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Text Mining of News Articles for Stock Price Predictions

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Problem Description

This work is focused on the relationship between the news articles (breaking news) and stock prices. The student will design and develop methods to analyze how and when the news articles influence the stock market. News articles about Norwegian oil related companies and stock prices from “BW Offshore Limited” (BWO), “DNO International” (DNO), “Frontline” (FRO), “Petroleum Geo-Services” (PGS), “Seadrill” (SDRL), “Sevan Marine” (SEVAN), “Siem Offshore” (SIOFF), “Statoil” (STL) and “TGS-NOPEC Geophysical Company” (TGS) will be crawled, preprocessed and the important features in the text will be extracted to effectively represent the news in a form that allows the application of computational techniques. This data will then be used to train text sense classifiers. A prototype system that employs such classifiers will be developed to support the trader in taking sell/buy decisions. Methods will be developed for automaticall sense-labeling of news that are informed by the correlation between the changes in the stock prices and the breaking news. Performance of the prototype decision support system will be compared with a chosen baseline method for trade-related decision making.

Assignment given: 15. January 2011
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Abstract

This thesis investigates the prediction of possible stock price changes immediately after news article publications. This is done by automatic analysis of these news articles. Some background information about financial trading theory and text mining is given in addition to an overview of earlier related research in the field of automatic news article analyzes with the purpose of predicting future stock prices.

In this thesis a system is designed and implemented to predict stock price trends for the time immediately after the publication of news articles. This system consists mainly of four components. The first component gathers news articles and stock prices automatically from internet. The second component prepares the news articles by sending them to some document preprocessing steps and finding relevant features before they are sent to a document representation process. The third component categorizes the news articles into predefined categories, and finally the fourth component applies appropriate trading strategies depending on the category of the news article.

This system requires a labeled data set to train the categorization component. This data set is labeled automatically on the basis of the price trends directly after the news article publication. An additional label refining step using clustering is added in an attempt to improve the labels given by the basic method of labeling by price trends.

The findings indicate that categorization of news articles into positive, neutral, and negative categories provides enough information for it to be used to forecast stock price trends. Experiments showed that the label refining method greatly improves the performance of the system. It was also shown that the timing of when to start the price trends used to label the data sets had a significant impact on the results. Trading simulations performed with the systems managed to gain positive returns (profits) on most of its trades. Some of the methods also managed to give better results than what trades performed with the manually labeled data set did.

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1 Introduction

News articles written about companies serve the purpose of spreading information about the companies, and this information then influence people either consciously or unconsciously in their decision process when trading in the stock market. Annual and quarterly earnings, dividend announcements, acquisitions, mergers, tender offers, stock splits, and major management changes, and any substantive items of unusual or non-recurrent nature are examples of news items that are useful for traders in their trading decisions. These types of news are usually published immediately as breaking news and are often given to the press directly from the companies. News articles with other kinds of information (e.g. political news) about companies are also important for traders, but they do not necessarily originate from the companies themselves. With the immense growth of the internet in the last decade, the amount of published news articles has experienced a similar rate of growth, which has increased the amount of both useful and not so useful information about each company.

Information published in news articles influence, in a varying degree, the decisions of the stock traders, especially if the given information is unexpected. It is important to analyze this information as fast as possible so it can be used as help for trading decisions by traders before the market has had time to adjust itself to the new information. This is a humongous task if done manually because of the immense amount of information and the speed of which new information is published. This means that an automatic system for analyzing news articles is needed.

Because of the internet, as mentioned above, there has been a huge growth of easily available textual information over the last decade in the form of documents, news, blogs, forums, emails, and etc. This increased amount of available textual information has lead to a research field devoted to knowledge discovery in unstructured data (textual data) known as text mining (Konchady, 2006). Text mining originates from the related field of data mining, which mines patterns from structured data instead of unstructured. It is also related to other fields like information retrieval, web mining, statistics, computational linguistics and natural language processing.

One important application of text mining is text sentiment analysis, also referred to as opinion mining. This technique tries to discover the sentiment of a written text. This can be used to categorize text documents into a set of predefined sentiment categories (e.g. positive or negative sentiment categories), or it can be used to give the text a grade on a given scale (e.g. giving a text about a movie review a score on a grade from one to ten). Sentiment analysis seems like a logical place to start when applying text mining to analyze news articles. This is because positive news articles should have a higher probability of positively influencing the stock price, while the opposite is true for negative articles.

1.1 Motivation

The main purpose of this thesis is to investigate if and how text mining techniques can be used to predicting the future trends of stock prices by analyzing news articles (breaking news). As we will see later in chapter 3, researchers have already performed similar studies. However, this is still a small field, but it is growing. There are more articles published on computational stock market prediction that uses numbers like stock price, volumes, company income, company cost, and so on, instead of textual information from news articles. It is important to investigate how stock markets react to breaking news because if we know this we can create fast computerized systems that automatically analysis new news articles before the market has had time to adjust itself to the new information. Doing this opens up the possibility for making much more profit on stock trades, if it works.

There are some novel features in the system developed in this thesis that distinguishes it from other existing articles in this field. The main difference is probably that it includes an extra process in hope of improving the sentiment labels annunciated to the articles by first linking them with the price trend for the related company after their publications (News followed by increased prices are positive and the opposite ones are negative). Three algorithms based on clustering techniques were added and compared for this extra step in an attempt to improve the automatic labeling process. This thesis also adds methods mentioned in other related and unrelated articles but which are not commonly used in these kinds of systems, like bigrams as features, feature reduction by using SVD, selecting only documents containing significant features and comparing the result with a manually labeled set.

1.2 Objectives and Hypotheses

The objectives and hypotheses for the thesis are formulated as follows.

Objectives

1- Study existing systems for automatically analyzing financial news articles with main focus on systems that uses the sentiment of news articles in their prediction of future price trends.
2- Investigate text mining methods that might be used in an attempt to create an improved system.
3- Design, implement and evaluate a system that uses sentiment analysis on news articles to automatically generate trading signals.

Hypothesizes

1- When the stock trading is done from signals generated from sentiment analysis of news articles, then the profit is better compared to what a random trader gives. Or in other words, a news based trader will give positive profits over time.
2- A classifier trained on an automatically created training set performs on the same level as humans at predicting how trends will move after news articles are published.
3- A training set of news articles for the sentiment classifier might be automatically created and labeled by looking at how the price for the related company changes after the article is published.
4- A training set created by looking at price trends after the news article is published is improved by running it by a clustering based algorithm for label refining.
5- The timing of when to start the price trend when it is used for labeling news articles for the training set is important. Starting the price trend a little before the news article is published gives better results since it is certain to capture the early price adjustments right after the news is published.

1.3 Report Outline

This thesis consists of seven chapters including the introduction and the conclusion. Chapter 2 explains some general background about trading theory (section 2.1) and about text mining (section 2.2) that are useful for understanding the following chapters. Chapter 3 gives an overview of some related research on the subject of news based trading systems. The general structure of the related systems are described and some of the more important and common aspects are described in more detail. Chapter 4 describes the framework developed in this thesis. Chapter 5 prepares the system for experimenting by choosing system parameters and explaining data handling and the experiment evaluation methods. In chapter 6 the conducted experiments are described and the experimental results are analyzed. The thesis concludes with a summary of experimental results and future research directions in chapter 7. Two appendixes are also included. Appendix A shows an example of a news article and its features, and appendix B show some examples of evaluation summaries.

2 Background

2.1 Trading Theory

This thesis assumes no prior knowledge of finance and trading theory on the part of the reader, it is therefore appropriate to provide some basic background of financial trading theory. This section explains some key financial trading concepts which should make it easier to understand the rest of this thesis.

2.1.1 Investing

This section briefly introduces some central concepts of investment theory. Its purpose is to give a basic understanding of how investment decisions are done on a basic level. In the field of finance, investment generally refers to the act of using capital (i.e. money) to buy some type of asset expected to generate a profit for the investor over time.

The focus of this report is on stocks, which is a specific type of financial asset, and how stock prices are affected by financial news articles. The theory discussed and developed in the following chapters in this thesis should in theory be possible to apply to many other types of liquid assets (a liquid asset is an asset that has many sellers and buyers). Examples of liquid assets are stocks, bonds[1], currencies[2], commodities[3] and mutual funds[4], but this thesis focuses only on stocks.

Stocks

A stock is a type of financial asset that denotes part ownership on the assets and profits of a company. It also entitles the owner of the stock to receive dividends if the company chooses to pay some of their profits to the shareholders. Typically, ownership of a stock also gives the investor a right to vote on corporate decisions at shareholder meetings.

Stock exchanges

Stocks are usually traded at one or more stock exchanges. The exchange receives an influx of orders to buy or sell a given volume of a stock at a given price, which are matched together making a trade when the price of a buy order matches the price of a sell order.

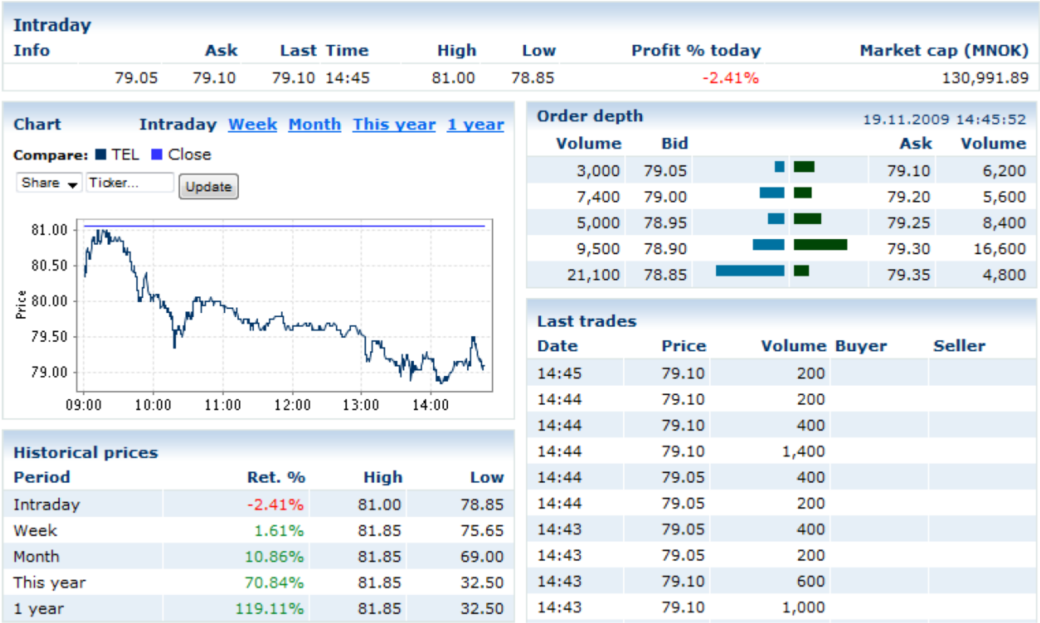
Historically, stock exchanges have been physical places where stock brokers placed orders to buy or sell stocks in person, but with the technological advances more and more stock exchanges have become purely electronical. The world's largest exchange, the New York Stock Exchange (NYSE), still has a physical trading floor (although most orders are now electronically entered) (New york stock exchange: Wikipedia). Another popular exchange, NASDAQ, is managed completely electronically (Berk & DeMarzo, 2007, s. 13). In Norway, the largest stock exchange is the Oslo Stock Exchange (OSE), which is where the stocks in this thesis are from, also trade stocks electronically (Oslo stock exchange: Wikipedia).

[1] A bond is a formal contract to repay borrowed money with interest at fixed intervals. (Arthur & Sheffrin, 2003)

[2] In economics, currency refers to physical objects generally accepted as a medium of exchange. (Currency: Wikipedia)

[3] Commodities are goods for which there is a demand, but which is supplied without qualitative differentiation across a market. A commodity is treated by the market as equivalent or nearly so no matter who produces it. Examples are petroleum and copper. (Arthur & Sheffrin, 2003)

[4] A mutual fund is a type of investment company that pools money from many investors and invests the money in stocks, bonds, money-market instruments, other securities, or even cash. (Mutual Funds: U.S Securities and Exchanges Commission)



Intraday

Info		Ask	Last	Time	High	Low	Profit % today	Market cap (MNOK)
	79.05	79.10	79.10	14:45	81.00	78.85	-2.41%	130,991.89

Order depth 19.11.2009 14:45:52

Volume	Bid	Ask	Volume
3,000	79.05	79.10	6,200
7,400	79.00	79.20	5,600
5,000	78.95	79.25	8,400
9,500	78.90	79.30	16,600
21,100	78.85	79.35	4,800

Historical prices

Period	Ret. %	High	Low
Intraday	-2.41%	81.00	78.85
Week	1.61%	81.85	75.65
Month	10.86%	81.85	69.00
This year	70.84%	81.85	32.50
1 year	119.11%	81.85	32.50

Last trades

Date	Price	Volume	Buyer	Seller
14:45	79.10	200		
14:44	79.10	200		
14:44	79.10	400		
14:44	79.10	1,400		
14:44	79.05	400		
14:44	79.05	200		
14:43	79.05	400		
14:43	79.05	200		
14:43	79.10	600		
14:43	79.10	1,000		

FIGURE 2.1: Information on stock (Telenor) traded on Oslo Stock Exchange

Basic stock information

FIGURE 2.1 shows an example of relevant information for a stock traded on the Oslo Stock Exchange, taken from the OSE website. The stock in the example is of the Norwegian corporation Telenor. Some of the information presented is:

- The current bidding price (the highest current buy order) and the asking price (the lowest current sell order).
- An order depth which shows what volumes of (number of) stocks has been ordered to buy or sell at a given price.
- The last trading price, which is the most recent price at which a buy and sell order were matched together to make a trade. There is also a list called “Last trades" which shows several of the most recent trades.
- The high and low prices show the highest and lowest prices at which the stocks have traded throughout the day.
- The “Profit % today" figure shows what percentage the price has moved since the last price traded, the close, of the previous day. This figure is commonly referred to as the intraday return from the given stocks.
- There is also a table called “Historical prices", where you can see the return from the stocks since last week, last month, the beginning of the current year and one year ago exactly. This table also shows the high and low prices over the respective time periods.
- The market capitalization figure shows the current total value of the company as measured by the last price at which it was traded multiplied by the total number of outstanding stocks in the company.

In addition to the figures given in this example, some other basic statistics of interesting includes:

- The volume of stocks that have been traded throughout the day. The volume of the traded stocks gives a good measure of the liquidity of the stock, indicating how easy it would be for any individual investor to buy or sell a large number of stocks in the market.
- The opening price, simply referred to as *open*, for the stock in that day (i.e. the price of the first trade of the stock in the trading day).

Ticker symbols

All stocks that are publicly traded are given a short abbreviation called a *ticker symbol* used to uniquely identify them on a particular market. Because a given ticker symbol may refer to a different stock on a different stock exchange, it is not uncommon to prefix the ticker symbol with an abbreviation that identifies the exchange on which it is traded in order to avoid confusion. TABLE 2.1contains a few examples of what ticker symbols are used to identify certain stocks.

Ticker symbol	Corporation	Stock exchange
GE	General Electric Co.	*NYSE*
GOOG	Google Inc.	*NASDAQ*
MSFT	Microsoft Corporation	*NASDAQ*
REC	Renewable Energy Corporation	*OSE*
STL	Statoil	*OSE, NYSE*
TEL	Telenor Group	*OSE*

TABLE 2.1 Examples of stock ticker symbols

Stock market indexes

A stock market index is a method of measuring the price movements of a collection of stocks. Different indexes measure different collections of stocks using different formulas. Indexes are useful to investors because they give a benchmark by which one can compare the returns of individual stocks.

The popular Dow Jones Industrial Average (DJIA) index measures the collective return of 30 large-cap (large market capitalization) stocks traded on either the NYSE or the NASDAQ, using a price weighting. This means it is computed by taking a weighted average of the prices of its 30 constituent stocks where each stock is weighted proportionally to its price.

Another heavily quoted index is the S&P 500 which until recently was a market-value weighted index composed of 500 large-cap stocks traded in the US. A market-value weighted index is computed as a weighted average where each component stock is weighted proportionally to its market capitalization. Since 2005, the index has transitioned from being market-valued to becoming oat-weighted, which in short means that only the capitalization of the stocks that are available for public trading are taken into account.

Stock options

A *stock option* is a type of financial contract whose value is tied to the future value of a stock. There are two main types of options:

Call option: A *call option* gives the owner of the *option* a right to purchase stocks at a given price (the strike price) on a given date in the future. If the actual market price of the stock is higher than the strike price at that time, he can then immediately sell the stocks to the market for a profit. If not, the option is valueless.

Put option: A *put option* is a similar contract, but instead of the right to buy, it gives the owner of the *option* a right to sell stocks at a given strike price on a given future date. This means its value at that date is equal to the difference between the strike price and the market price (i.e. the lower the market price the better).

Stock options are traded on most major stock exchanges. To illustrate with an example, consider the STL0M145 option contract traded on the OSE. This is a *put option* which gives the owner the right to sell shares of Statoil (STL) for 145 NOK in January of 2010. As of 28.11.09 this *option* was last traded at 7.50 NOK, meaning it will only be profitable if the share price of Statoil in January 2010 is lower than 145 – 7.5 = 137.5.

Stock options are popular to investors because they can potentially make a large profit on a small investment. However, they are also a lot more risky than just buying the stock, because they can easily loose all their value.

Long and Short Positions

Long position

As already discussed, an investment in an asset such as stocks usually involves the following steps: buying the stock, owning the stock for some period of time, and finally selling it back to the market. In financial terms, investing in this manner is known as taking a *long position* in the stock. More generally, an investor is said to have a *long position* in a stock when he owns one or more units of the stock.

Short position

Sometimes, an investor might believe that a given stock will have a negative return in the future (that the price will fall). As mentioned earlier, one way to profit from such a downward move might be to buy a *put option* for the stock. Another way to profit from falling prices is by taking a *short position* in the stock. Taking a short position in a stock generally involves the following steps:

1. First, you borrow the amount of stocks you wish to go short. For a private investor, this stock loan is typically carried out automatically through their stock broker.
2. Immediately after borrowing the stocks, you sell them to the market for the current price p_0.
3. After some time, hopefully, the price has fallen down and you buy the same amount of stocks back from the market at the lower price p_1.
4. You return the stocks back to their original owner step 1.

As you can see, this investment is profitable as long as $p_0 > p_1$ (i.e. the share price has gone lower).

Risk comparison

The potential for losing money is far greater for the short position than for the long position. This is because the future price of the stock can grow unboundedly high, meaning that in an extreme scenario you might have to pay many times the original price to repurchase the stocks, giving you a loss of far more than 100%. With a long position, there is no way you could lose more than 100% of the money you invest, and this would only happen in the scenario that the company went bankrupt (unless you're using leverage, which will be discussed shortly).

2.1.2 Technical Analysis

In its purest form, technical analysis only uses historical and current price and volume values to predict future price moves. This means that technical analysis mainly uses models and trading rules based on price and volume transformations, such as the moving averages[5], relative strength index[6] (RSI) and price correlations. It can also look for chart patterns[7], such as “head and shoulders”[8], triangles, trend lines and Elliot waves[9]. Some different definitions of technical analysis, taken from different sources, are:

> Technical analysis is the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends. (Murphy, 1999)
>
> Technical analysis is a security analysis discipline for forecasting the future direction of prices through the study of past market data, primarily price and volume. (Technical analysis: Wikipedia)
>
> Technical Analysis is the science of recording, usually in graphic form, the actual history of trading (price changes, volume of transactions, etc.) in a certain stock or in "the Averages" and then deducing from that pictured history the probable future trend. (Meyers, 2002)

Principles

Classical technical analysis are based upon three main principles, and they are; (I) Market action discounts everything, (II) Prices move in trends, and (III) History tends to repeat itself.

Market Action Discounts Everything

The statement "market action discounts everything" forms what is probably the most important cornerstone of technical analysis. The technician believes that anything that can possibly affect the price - fundamentally, politically, psychologically, or otherwise - is automatically reflected in the price of the market.

Prices Move In Trends

The concept of trends is absolutely essential to the technical approach. Technicians say that markets trend up, down, or sideways (flat). This basic definition of price trends is the one put forward by Dow Theory.

[5] Moving average: Given a series of numbers and a fixed subset size, the moving average can be found by first calculating the average of the first subset. Next the subset is shifted one step forward, and the average of this new subset is calculated. This process is repeated over the entire data series. A line is then plotted by connecting these calculated values to create the moving average.

[6] RSI measure the velocity and magnitude of directional price movements. The RSI is classified as a momentum oscillator, where the momentum is the rate of the rise or fall in price.

[7] Chart patterns are a pattern within price charts. They are patterns which naturally occur and repeats over time. Chart patterns are used as either reversal or continuation signals.

[8] Head and Shoulders patterns consist of a left shoulder, a head (higher peek than the shoulders), and a right shoulder and a line drawn as the neckline between the shoulder. The price is likely to reverse its direction if the price crosses over the neckline after the left shoulder.

[9] Elliott proposed that market prices unfold in specific patterns, which practitioners today call Elliott waves. Elliott stated that "because man is subject to rhythmical procedure, calculations having to do with his activities can be projected far into the future with a justification and certainty heretofore unattainable. (Elliott, 1994)

Prices move in trends and trends tend to continue until something happens that changes the demand and supply balance. This can be seen as an adaption of Newton's first law, "A body persist its state of rest or of uniform motion unless acted upon by an external unbalanced force". These "external" forces can be technical signals such as reversal patterns or breakouts. The goal in this trend-following approach is for the technician to get in on an existing trend as early as possible and ride on it until it shows signs of reversing.

History Tends to Repeat Itself

Technicians believe that investors collectively repeat the behavior of the investors that preceded them. Because investor behavior repeats itself so often, technicians believe that recognizable and often predictable patterns will emerge. The key to understanding the future therefore lies in studying the past.

2.1.3 Fundamental Analysis

Fundamental analysis of a business involves analyzing its financial data to get some insight on whether it is overvalued or undervalued. This is done by analyzing historical and present economic data to do a financial forecast of the business. The intrinsic value of the business is found by doing a fundamental analysis which consist of three main steps; (I) economic analysis, (II) industry analysis and (III) company analysis. If the intrinsic value is higher than the market price it is recommended to buy stocks, if it is equal to market price then it is best to hold your shares, and if it is less than the market price then it’s a selling signal.

Fundamental analysis maintains that markets may misprice an asset in the short run but that the "correct" price will eventually be reached. Profits can be made by trading the mispriced security and then waiting for the market to recognize its "mistake" and reprises the security. (Fundamental analysis: Wikipedia)

Procedures

All publicly traded companies release reports on their financial performance on a regular basis (usually once every quarter with a larger annual report). These reports typically include different types of financial statements, the most significant being: the balance sheet[10], the income statement[11], the cash flow statement[12] and dividend paid. The fundamental analysis of a business' health starts with analysis of some of these financial statements.

The determined growth rates and risk levels are used in various valuation models. The foremost is the discounted cash flow model[13], which calculates the present value of the future. The amount of debt is

[10] A balance sheet is often described as a "snapshot of a company's financial condition". It is a summary of the financial balances of a company. (Berk & DeMarzo, 2007)

[11] Income statement is a company's financial statement that indicates how the revenue is transformed into the net income. It displays the revenues for a specified time period, and the cost and expenses charged against these revenues, including write-offs and taxes. (Berk & DeMarzo, 2007)

[12] Cash flow statements are essentially concerned with the flow of cash in and cash out of the business. It is a financial statement that shows how changes in balance sheets and income affect cash flow. (Berk & DeMarzo, 2007)

[13] Discounted cash flow (DCF) analysis is a method of valuing a project, company, or asset using the concepts of the time value of money. All future cash flows are estimated and discounted and added together to give their present value. (Discounted cash flow: Wikipedia) (Jennergren, 2008)

also a major consideration in determining a company's health. It can be quickly assessed using the debt to equity ratio[14] and the current ratio[15]. (Fundamental analysis: Wikipedia)

Some other methods often used when performing a fundamental analysis are the popular P/E and PEG ratios. The P/E (price/earnings) ratio is the price of one share divided on the company profit per share, while the PEG (Price/Earnings to Growth ratio) includes the feature expected growth of the company so a high- growing company won't appear overvalued to others.

2.1.4 Efficient-Market Hypothesis

The efficient-market hypothesis (EMH) states that market prices always reflects all available information, or in other words, financial markets are informational efficient. This means that no one can consistently achieve greater returns than that of the average market returns, not even if they are given all the publically published information that are available at the time of investment.

The EMH is divided into three different hypotheses: weak form efficiency, semi-strong form efficiency, and strong form efficiency, each of which has different implications for how the market works.

Weak form efficiency states that future prices cannot be predicted from analyzing historical prices. In other words, excess returns, or profits, cannot be gained in the long run by using investment strategies based on historical prices or other historical forms of data. This means that technical analysis will not be able to consistently produce excess returns. This is because one of the main principles vital to technical analysis states that history tends to repeat itself. It states that stock prices exhibit no serial dependencies, meaning that there exist no "patterns" to asset prices, which is especially important for chartists which is a subfield under technical analysis. Weak form efficiency states that all future price movements follow a random walk, unless there is some change in some fundamental information. It does not state that prices adjust immediately in the advent of new fundamental information, which means that some forms of Fundamental analysis and also news article analysis might provide excess returns. This is because they trades on new information and does not use any historical information to look for patterns.

Semi-strong form efficiency implies that share prices adjust in an unbiased fashion to new publicly available information very rapidly such that no excess returns can be earned by trading on that information. This form of EMH implies that fundamental analysis, technical analysis nor news trading will be able to reliably produce excess return over time.

In strong-form efficiency, stock prices reflect all information, public and private, and no one can earn excess returns. According to this form of EMH, those traders that are consistently getting profitable return are only lucky since they are among the randomly selected few that are.

There has been a lot of criticism against the EMH. Manly because it assumes that investors always behave rationally, but many behavioral economists argue that the presences of cognitive biases (such

[14] The debt-to-equity ratio (D/E) is a financial ratio indicating the relative proportion of shareholders' equity and debt used to finance a company's assets. (Debt-to-equity ratio: Wikipedia)

[15] Current ratio is a financial ratio that measures whether or not a firm has enough resources to pay its debts over the next 12 months. (Current ratio: Wikipedia)

as confirmation bias[16], the bandwagon effect[17], hyperbolic discounting[18], and irrational escalation of commitment[19]) negate the validity of this assumption.

Fore hypothesis 1 in this thesis to be true, the EMH has to be false. If it is not, only the week form EMH can be true. If the semi-strong or the strong form EMH is true, then hypothesis 1 will be false.

2.1.5 Random Walk Theory

The theory of the random walk hypothesis (Cootner, 1964) claims that stock market prices changes according to a random walk and, consequently, prices cannot be predicted. Therefore, it is impossible to consistently outperform the average market return. This theory is based on the efficient-market hypothesis (EMH), which says that prices fluctuate randomly about their intrinsic value. It also holds that the best trading strategy to follow would be a simple "buy and hold" instead of any attempt to "beat the market".

The primary experiment conducted for this theory was to draw a price graph randomly and have some chartists (technical analysts that analysis price charts) analyze it. The price graph started from an initial value of fifty dollars and all future movements (ups and downs) was chosen by performing a coin flip (fifty-fifty chance for each movement). The chartist, after analyzing the graph, found signs that made him recommend buying. This is then used to argue that the market and stocks could be just as random as flipping a coin.

There have been many researchers that have attempted to produce falsifications of the EMH and the random walk hypothesis, with mixed results. One of the most commonly mentioned is the book "A Non-Random Walk Down Wall Street" (Lo & MacKinlay, 1999) which describes a statistical model claiming to provided significant empirical evidence against the random walk theory.

2.1.6 News Articles Influence on Stock Markets

The basic strategy for news based trading is to buy a stock from companies that has just gotten good news published about them self, or short sell on bad news. Strong and unexpected positive or negative events provide enormous volatility in a stock and gives therefore great chances for quick profits, or losses if they are interpreted wrongly. Determining whether news was "good" (positive) or "bad" (negative) should be determined by the price trend after the news article was published because the market reaction may not match the tone of the news itself. The most common cause for this is when rumors or estimates of the event, like those issued by market and industry analysts, were already circulated before the official news release, and prices have already adjusted them self in anticipation of the official news release.

[16] Confirmation bias is a tendency people have to favor information that confirms their preconceptions or hypotheses regardless of whether the information is true. Consequently, people gathers evidence and recall information from memory in a selectively fashion. (Plous, 1993)

[17] The bandwagon effect states that people often do and believe things merely because many other people do and believe the same things. (Bandwagon effect: Wikipedia)

[18] Given two similar rewards the hyperbolic discounting states that humans show a preference for the one that arrives sooner rather than the one that arrives later. Humans are said to discount the value of the later reward, by a factor that increases with the length of the delay. (Hyperbolic discounting: Wikipedia)

[19] Irrational escalation of commitment is a term frequently used to refer to a situation in which people can make irrational decisions based upon rational decisions in the past or to justify actions already taken. It's a phenomenon where people justify increased investment in a decision, based on the cumulative prior investment, despite new evidence suggesting that the cost, starting today, of continuing the decision outweighs the expected benefit. (Escalation of commitment: Wikipedia)

For it to be possible for traders trading on news articles to gain excess returns over time all but the week form efficiency of the EMH (see section 2.1.4) has to be false. If the semi strong or the strong form efficiency EMH is true then it is impossible to gain excess returns over time with news based trading.

The number of traded stocks has been shown to be positively or negatively affected by economic news publications (Chan, Chui, & Kwok, 2001). It is also found that both political and economical news articles affect trading activities such as price volatility, number of stocks traded, and trade frequency (Chan, Chui, & Kwok, 2001). Country specific news articles occupying at least two columns on The New York Times front pages has been shown to affect the trading actions of closed-end country funds[20]. News articles appearing on the front page of the Shout China Morning Post has been shown to increase the volatility in the Hong Kong stock market (Chan & John-Wei, 1996). The number of relevant headlines reported by Dow Jones and Reuter's News Service per time unit has also been shown to affect the volume (volatility) on the related stocks (Mitchell & Mulherin, 1994) (Berry & Howe, 1994). All this is strong evidence against the EMH, at least for the strong and semi-strong forms. This means that there should be possible to create a system that automatically analysis news articles and returns a trade signal (buy, hold, or sell) based the results from its analysis.

[20] A closed-end fund is a collective investment scheme with a limited number of shares. It is called a closed-end fund because new shares are rarely issued once the fund has launched, and because shares are not normally redeemable for cash or securities until the fund liquidates. (Closed-end fund: Wikipedia) A country fund is an international mutual fund with a portfolio that consists entirely of securities, generally stocks, of companies located exclusively in a given country. (Country fund: Investopedia) (closed-end-country-funds: financial-education) (Klibanoff, Lamont, & Wizman, 1998)

2.2 Relevant Text Mining Methods

This section briefly describes the text mining methods used by the trade support and analysis systems. It`s primarily goal is to describe the methods used or planed to be used in the system developed in this thesis, but it also describes some methods not used in this system but which are used by other news based trade support systems that are described in chapter 3.

Text mining (Konchady, 2006) (Text mining: Wikipedia) refers to the process of deriving high-quality information from text. High quality in text mining usually refers to some combination of relevance, novelty, and interestingness. Text mining usually involves the process of structuring the input text, deriving patterns within the structured data, and finally evaluation and interpretation of the output. Typical text mining tasks include text categorization[21], text clustering[22], concept/entity extraction, production of granular taxonomies, sentiment analysis[23], document summarization[24], and entity relation modeling. Text mining has been applied in many different areas, some being; biomedical applications (e.g. identification of biological entities, association of gene clusters, automatic extraction of protein interactions and associations of proteins to functional concepts), software and applications, online media applications, marketing applications (e.g. customer relationship management), and sentiment analysis (e.g. customer sentiments on movies and products).

2.2.1 Preprocessing

Text preprocessing is the process of making clear each language structure and to eliminate as much as possible the language dependent factors. (Wang & Wang, 2005) There are many different tasks under preprocessing, but some of the most common ones are tokenization, stop-word removal and word stemming.

Tokenizing

Tokenization is the process of splitting a text stream into symbols, words, phrases, or other meaningful elements called tokens. These tokens are used further text mining techniques. Word tokens are typically sent to preprocessing stages like stop-word removal and stemming, which are described later. They are also used as input for feature extraction processes.

There are many ways of tokenizing text streams into tokens. A simple method would be just to split the text on blank spaces, but better methods also takes punctuation and other sings into consideration. The tokenizing method used in this thesis would tokenize the following text string:

"Hello! This is test number 11. It tests the word_punct-tokenizer!@ test66"

[21] The Document categorization (classification) task is to assign an electronic document to one or more categories, based on its contents. (Document classification: Wikipedia)

[22] Text clustering is closely related to the concept of data clustering. Document clustering is a more specific technique for unsupervised document organization, automatic topic extraction and fast information retrieval or filtering. (Document clustering: Wikipedia) Clustering is the assignment of a set of observations into subsets (called clusters) so that observations in the same cluster are similar in some sense. (Cluster analysis: Wikipedia)

[23] Sentiment analysis aims to determine the attitude of a speaker or a writer with respect to some topic or the overall tonality of a document. (Sentiment analysis: Wikipedia)

[24] Automatic summarization is the computation of a shortened version of the original text. The product of this procedure still contains the most important parts. (Automatic summarization: Wikipedia)

First by splitting it on blank space, then this is followed by splitting it on most special characters. The tokenized string would then consist of the following tokens.

> ['Hello', '!', 'This', 'is', 'test', 'number', '11', '.', 'It', 'tests', 'the', 'word_punct', '-', 'tokenizer', '!@', 'test66']

Stop-Word Removal

Stop words are high frequency words of a language that don't carry any significant information on their own. These words are often removed at the preprocessing stage to reduce the number of features (se section 2.2.2 for features), thus reducing the amount of noise. However, stop words can together with other words contain a significant amount of information. Which means that in some situations, like when searching for phrases (e.g. "To be or not to be") or names (e.g. "The The" or "The Who"), the stop-words are sometimes kept and not removed. Closed class words like articles, pronouns, prepositions and conjunctions are usually included in stop-words lists. Some of the more frequently used open class words like auxiliary verbs are also included. It is also possible to create domain dependant stop word lists by filtering out high and low frequency words, or by using some statistical measure like information gain or chi-square to filter out the less informative words. During the removal process all the words that exist in the given stop word list are removed from the source documents.

Stemming

In linguistic morphology, stemming is the reduction of a word from its inflected form to its root, stem or base form. The stem does not need to be the words morphological root, it`s usually enough that related words map to the same stem, even if this stem is not in itself a valid root. It is a common procedure to use in information retrieval, natural language processing and other methods dealing with text analysis to discover the semantic similarity between the different morphological variants of a word. This means that and article that for example uses the word "walks" and another using the word "walking" will both have their word reduced to its root which is for both of them "walk". By doing this they have both gained a similar feature instead of having two features that the computer would see as totally different even when they for humans clearly have a high semantic similarity. Supporters for word stemming argue that it has the effect of reducing the dimensionality of features which makes the data less sparse and faster to work with, and that it can be helpful to promote the effectiveness of a text classifier. But some experimental results showed that stemming sometimes might be harmful to the effectiveness of a text classifier(Baker & McCallum, 1998).

Some example of words that are or might be stemmed:

> Stemmer, stemming, stemmed → stem
> Cats, catty, catlike → cat
> Fishing, fishes, fished, fisher → fish

The best known stemming algorithm is probably the Porter stemmer. It uses a set of language specific rules to transform a word into its base form. However in this paper a different stemmer for Norwegian is written in the Snowball language developed by Porter. Snowball is a string-handling programming language where the rules for the stemming algorithm can be easily expressed in a natural way.

2.2.2 Features Types

Before text documents can be analyzed by text mining techniques, they must undergo a special processing step known as feature extraction. This process takes the preprocessed text documents and produces a set of features representing each document. Text features may be surface level lexical features, or semantic or other higher-level features. Surface level lexical features are word–based features that can be observed directly in the documents. Semantic features or higher-level features are extracted from the surface level lexical features. Statistical techniques, such as singular value decomposition (SVD), which is mentioned later in this chapter, topic modeling, and random projection, are important in solving this kind of problem. Higher-order features can greatly improve the quality of information retrieval, classification, and clustering tasks. These higher-order features are also often used as feature reduction techniques.

Unigrams

Unigrams are N-Grams[25] of size one, ore in other words, they consists of one single word. Another name used for unigram features are bag of words feature sets. Feature sets made from unigrams are made of all the selected single words that are left after the documents preprocessing steps. Despite its simplicity, this feature type has proven successful in text classification and word sense disambiguation (Mooney, 1996).

Bigrams

Bigrams are N-Grams of size two. Bigrams are a consecutive sequence of two words, and are very commonly used as the basis for simple statistical analysis of text. Bigrams captures more of the underlying sentence structure and contain more information than what unigrams do. This might help to improve the classification of the news article sentiment. Take the following imaginative articles:

D1: “X has changed their recommendation for company Y from sell to buy.”
D2: “X has changed their recommendation for company Y from buy to sell.”

The unigram representations of these two documents are exactly the same, but their sentiment are clearly not the same. However, by using bigrams, four following bigrams; “from sell”, “to buy”, “from buy”, and “to sell” are different. These features are therefore important in classifying the sentiment of the articles D1 and D2.

Noun Phrases

A noun phrase is a phrase based on nouns, pronouns, or other noun-like words, and it can optionally be accompanied by modifiers such as adjectives. Noun phrases normally consist of a head noun, which is optionally modified. Some examples of noun phrases are: blue car, where I live, blond girl, and the butler.

Noun phrases can be used to get more informative features than only single words and less important word are not included as features. To be able to extract noun phrases the text has to be tagged with a part-of-speech tagger(Part-of-speech tagging: Wikipedia) first. In a tagged document each word is tagged with tokens like noun, verb, adjective, etc. When the document is tagged the tags can be used to extract noun phrases.

[25] An N-Gram is a subsequence of n items from a given sequence. In this thesis the items are words.

Proper Nouns

Proper nouns(Mark & Larry, 2005), also called proper names, are nouns that represent unique entities, such as New York, John Smith, or Microsoft. They are distinguished from common nouns which describe classes of entities, such as the entities city, planet, person or corporation. Proper nouns are usually capitalized in English and most other languages using the Latin alphabet. Proper nouns are a subset of the set of noun phrases.

Name Entities

Name entities are special name entities, such as person names, locations, and organizations, in text documents. It is somewhat similar to proper nouns, but not as strict. Name entities can also include dates, times, and other numerical information. Name entities are often found by using statistical learning systems.

2.2.3 Feature Selection Metrics (CHI)

Feature selection is crucial to make the classification tasks more efficient and precise because textual data contains a very high-dimensional degree of features. Thus feature selection is a common way to reduce this high-dimensionality by only selecting the most important features. Some common feature selection matrices are information gain[26], mutual information[27], odds ratio[28], term strength[29], correlation coefficient, and chi-square (Taşcı & Güngör, 2008) (Forman, 2003). In this thesis we have chosen chi-square (CHI). The CHI does not give the best results of the feature selection methods, but it is among the better. It can also work with more than two values, and this thesis uses three.

Chi-Square Statistic (CHI)

A chi-square (X^2) statistic is used as a test of independence between each feature and the categories. When the chi-squared value is zero it means that the feature is independent of the category and the larger it gets the more dependent it is on the category. Feature selection can thus be done by only selecting features that has ha chi-square value higher than a given threshold, while the rest of the features can be discarded since they are independent of the categories, which means they have no significance.

To find each terms CHI value a contingency table is needed for each of them. Since this thesis operates with three categories, 2×3 contingency tables are constructed to determine the terms CHI values. This is in fact similar to a chi-square distribution with two degrees of freedom to judge extremeness. The chi-square value is found by the following formula:

[26] Information gain measures the number of bits of information obtained for category prediction by knowing the presence or absence of a term/feature in a document.

[27] The mutual information of two random variables is a quantity that measures the mutual dependence of the two variables. If the mutual information score is 0, then the two random variables are independent. (Mutual information: Wikipedia)

[28] The odds ratio is a measure of effect size, describing the strength of association or non-independence between two binary data values. (Odds ratio: Wikipedia) Effect size is a measure of the strength of the relationship between two variables in a statistical population, or a sample-based estimate of that quantity.

[29] Term strength estimates the term/feature importance based on how commonly a term is likely to appear in closely related documents. It uses a training set of documents to find document pairs that has a similarity score above a given threshold.

$$CHI = \sum \frac{(F_0 - F_e)^2}{F_e}$$

Here F_0 denotes the frequency of the observed data, and the F_e denotes the frequency of the expected values. The 2×3 contingency table used for this calculation looks something like this:

	Positive	Neutral	Negative	Row Totals
Category have feature	A	B	C	A+B+C
Category do not have feature	D	E	F	S+E+F
Column Totals	A+D	B+E	C+F	Q+B+C+D+E+F=N

TABLE 2.2: CHI contingency table

In TABLE 2.2 the cells A, B, and C shows how many documents that contains the given feature for each of the three categories, positive, neutral and negative has. The cells D, E, and F on the other hand show how many documents that does not contain the given feature. These cells contain the observed values F_0.

The next step is to calculate the expected values for each cell in the contingency table. This can be done by multiplying the row totals with the column totals and dividing it on the grand total. As an example, the calculation for the expected value for cell A looks like this:

$$Expected\ value(A) = \frac{(A + B + C) \times (A + D)}{N}$$

The expected value is found for each of the cells, then $(F_0 – F_e)^2/F_e$ is also found for each cell, and then they are summed up to get the CHI value. Then the degrees of freedom are found by this formula:

$$Degrees\ of\ Freedom = (columns - 1)(rows - 1)$$

And the chi-square calculation used in this thesis has 2 degrees of freedom. The minimum CHI value a term can have for it to still be significant is 5.991. If a term has a value less than this it means it is independent, and thus not of any importance when categorizing the documents. This value is found by looking up in a chi-square distribution table where alpha is chosen to be 0.05 and the degrees of freedom that was found earlier is 2.

The chi-square values are normalized, however this normalization breaks down and behaves erratically if any cell in the contingency table is lightly populated (less than five), which is the case for low frequency terms. This is simply solved in this thesis by giving all terms that has a cell with a value less than five a CHI value of zero.

2.2.4 Feature Reduction (SVD)

Feature reduction is as the name implies the process of reducing the number of features that are used for representing text documents. This is an important process since to many features affect the performance of classifiers and other text mining methods like document clustering and similarity measures. Feature reduction can be done by a simple feature selection process where the best features are selected and the rest are removed, or it is possible to fit methods that discover latent variables as feature reduction methods. Methods that discover latent variables are latent semantic analysis (LSA) (Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990) which uses singular value decomposition (SVD) (Golub & Kahan, 1965), random projection[30] and latent dirichlet allocation[31] (LDA).

Singular Value Decomposition (SVD)

SVD is a matrix factorization method which in text mining is usually used in LSA as a well known and successful dimensionality reduction technique. When SVD is used as a feature reduction technique it approximates the initial feature-document matrix by a matrix with a much smaller size. This news smaller matrix does no longer represent the same features as in the original feature-document matrix but instead it represents latent features.

SVD decomposes a term-context matrix X of size *(f × d)* (f is equal to the number of features and d is the number of documents) into three matrices:

$$SVD(X) = USV^T$$

Where, matrices U and V contain the left and right singular vectors of X and S is a matrix of singular values of X (Spence, Insel, & Friedberg, 2000).

- U is a matrix of size *(f × f)*. The left singular vectors in U consist of orthogonal columns that are eigenvectors of XX^T. Rows in this matrix represent the meaning of terms based on their co-occurrences with other terms.
- S is a diagonal matrix of size (*f × d)* where all entries except the diagonal are zeroes. The diagonal values of S are referred to as singular values, and they indicate the importance of each dimension in the corresponding column and row space in matrix X. Diagonal values in S are arranged in descending order.
- V is a matrix of size *(d × d)*. The right singular vectors in V consist of orthogonal columns that are eigenvectors of X^TX matrix. Rows in this matrix represent the meaning of contexts based on other contexts that they share terms with.

[30] Random projection projects the data onto a random lower-dimensional orthogonal subspace. The orthogonal high-dimensional data is projected onto a lower-dimensional subspace using a random matrix whose columns have unit lengths. Random projection is less computational expensive than principal component analysis and SVD. (Bingham & Mannila, 2001)

[31] In LDA, each document may be viewed as a mixture of various topics. (Blei, Ng, & Jordan, 2003)

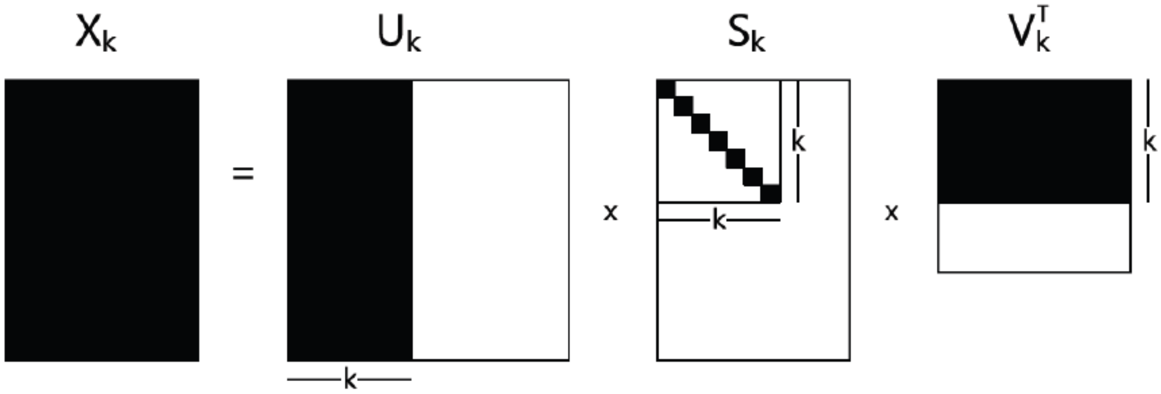


FIGURE 2.2 Truncation of matrices obtained through SVD.

The goal of LSA is to get a reduced matrix that contains much the same information as the original matrix X, but represented in fewer dimensions (k). This is achieved by selecting first k significant singular values from matrix S or by setting all its diagonal entries beyond k+1 to zeros. This has the effect of reducing the dimensionality of matrix X to k dimensions. This is shown in FIGURE 2.2.

The reduced matrix X no longer represents the actual words that occur in a text, but rather dimensions that suggest underlying/latent concepts. This has the effect of converting a surface level lexical feature space into a concept level semantic space which allows computations based on higher level conceptual meanings of features rather than their surface forms.

The truncated matrices are used either separately or in combination with each other. The truncated matrices ($f \times k$) U, ($k \times k$) S and ($k \times d$) V^t can be combined to get a new $f \times d$ matrix that is and approximation of the original $f \times d$ X matrix only with fewer dimensions in it. However, to get a matrix consisting of only k features, which is the main purpose of using SVD in this thesis, the $k \times d$ matrix SV^t where $k < f$ is used instead if the ($f \times d$) X matrix. This means that the documents are represented by *k* features instead of *f* features.

2.2.5 Document Representation

In order to reduce the complexity of text documents and make them easier to work with, the documents has to be transformed from the full text version to a document vector which describes the contents of the document. A document might be represented as a collection of features/terms: words, stems, phrases, or other units derived or inferred from the document text. These terms are usually weighted to indicate their importance. (Strzalkowski, 1994)

Vector space model

In text mining and information retrieval the predominant representation of text documents is based on a vector space model where the dimensions correspond to features extracted from the text. The vector space model (Salton, Wong, & Yang, 1975) is an algebraic model for representing text documents, or other objects, as vectors of features that identifies each of the text documents in the model. Documents are represented as vectors, and each dimension in the document vector corresponds to a unique feature. If a feature does not exist in a document its value is set to zero in the document vector, but if it exist in the document it’s given a value. This value is calculated by a term weighting method. Feature values are often based on term frequencies and frequency distribution factors. One of the best known term weighting schemes is tf-idf, which is explained in the following section.

In TABLE 2.3 the vector space model for four sentences are shown. The sentences are:

- Q: Gold silver truck
- D1: Shipment of gold damaged in a fire
- D2: Delivery of silver arrived in a silver truck
- D3: Shipment of gold arrived in a truck

	Counts	Counts	Counts	Counts
Terms	Q	D1	D2	D3
A	0	1	1	1
Arrived	0	0	1	1
Damaged	0	1	0	0
Delivery	0	0	1	0
Fire	0	1	0	0
Gold	1	1	0	1
in	0	1	1	1
Of	0	1	1	1
Siler	1	0	2	0
shipment	0	1	0	1
Truck	1	0	1	1

TABLE 2.3Vector model with term counts as weights

Vector space models make it easy to calculate similarities between documents by using method like the cosine similarity, which is explained in the following section. It also makes it easy to use each document vector as input for classification an algorithm.

Some limitations of the vector space models are that very long documents are poorly represented because they have poor similarity values because of a small scalar product and a large dimensionality. The order in which the terms appear in the documents is lost.

Term weighting (tf-idf)

There are three main factors usually accounted for in term different weighting schemas: term (feature) frequency factor, collection frequency factor and length normalization factor. Term frequency factor is the frequency of the term in a given document and collection frequency is the number of other documents in the collection that contain the term. The result from these two factors is important to normalize on the length since text documents vary greatly in length. These three factor are multiplied together to make the resulting term weight.

The tf–idf weight (term frequency–inverse document frequency) is the most used term weighting method in information retrieval and text mining. The term weight is a statistical measure used to evaluate how important a feature/term is to a document. The tf-idf weight increase in proportion to the number of times a feature appears in a document but is offset by the number of number of documents it appears in. The formula for the tf-idf is:

$$(td - idf)_{i,j} = tf_{i,j} \times idf_i$$

Where $tf_{i,j}$ is the term frequency of term i in document j, and idf$_i$ is the collection frequency factor. The formula for the tf$_{i,j}$ is:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

Where $n_{i,j}$ is the number of occurrences (term count) of the considered term t_i in document d_j, and $\sum_k n_{k,j}$ is the sum of all terms in document d_j, or in other word, the size of document d_j. The reason why the term count is dividend on the length of the document is to normalize the document on the length. If this were not done, the term weight would have a bias towards longer documents.

The inverse document frequency (idf_i) is obtained by dividing the total number of documents by the number of documents containing the term, and then taking the logarithm of that. It is a measure of the general importance of the term. The formula for the idf_i is as follows:

$$idf_i = \log \frac{|D|}{1+|\{j : t_i \in d_j\}|}$$

Where, |D| is the total number of documents in the collection and $|\{j : t_i \in d_j\}|$ is the number of document in which the term/feature t_i appears. If the term t_i does not exist in the collection it will lead to a division by zero. It is therefore more common to use $1 + |\{j : t_i \in d_j\}|$.

The higher tf-idf value a term gets, the more important it is. A high value is reached when the term frequency in the given document is high and when there are few other documents in the collection containing the given term/feature. This term weighting method tends therefore to filter out common terms by giving them a very low value.

In the gray area in TABLE 2.4 we can see the tf-idf scores for the example sentences motioned in the above section about the vector space model.

		tf_i				TF-DF			
Terms	Q	D1	D2	D3	idf_i	Q	D1	D2	D3
A	0	0.1429	0.125	0.1429	0	0	0	0	0
Arrived	0	0	0.125	0.1429	0.1761	0	0	0.022	0.0252
Damaged	0	0.1429	0	0	0.4771	0	0.0682	0	0
Delivery	0	0	0.125	0	0.4771	0	0	0.0596	0
Fire	0	0.1429	0	0	0.4771	0	0.0682	0	0
Gold	0.3333	0.1429	0	0.1429	0.1761	0.0586	0.0252	0	0.0252
in	0	0.1429	0.125	0.1429	0	0	0	0	0
Of	0	0.1429	0.125	0.1429	0	0	0	0	0
Siler	0.3333	0	0.25	0	0.4771	0.1589	0	0.1193	0
shipment	0	0.1429	0	0.1429	0.1761	0	0.0252	0	0.0252
Truck	0.3333	0	0.125	0.1429	0.1761	0.0586	0	0.022	0.0252

TABLE 2.4: Vector model with tf-idf scores

Similarity measure (cosine similarity)

Cosine similarity is used to calculate the similarity between two vectors, document vectors in this case. This is done by measuring the cosine of the angel between the two vectors. FIGURE 2.3 show two document vectors, and it's the angle between them that is measured. When the angle between the two vectors are zero it means that they are identical, and the bigger that the angel between them is the more dissimilar they are. The cosine is equal to one when the document vectors ere identical, and it gets lower the more unlike each other they are. In text mining (and other fields working with text documents, e.g. information retrieval) the cosine similarity between two documents will range from zero to one, since the term frequencies cannot be negative, thus the angle between two term frequency vectors cannot be greater than 90°. Cosine similarity is often used to compare documents in text mining and in information retrieval. In addition, it is used to measure cohesion within clusters in the field of Data Mining.

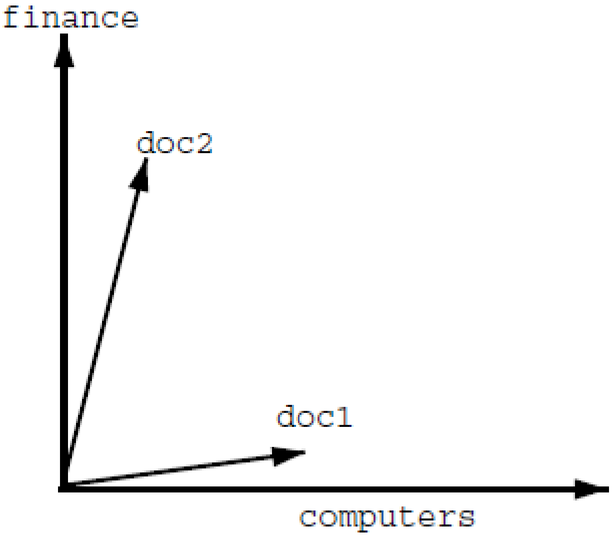


FIGURE 2.3: document vectors in vector space

The cosine formula is derived from the Euclidian dot product formula:

$$A \cdot B = ||A|| \, ||B|| \, cos\theta$$

Given two document vectors, A and B, of feature weights, the cosine similarity, θ, is represented using a dot product and magnitude as:

$$Similarity = cos\theta = \frac{A \cdot B}{||A|| \, ||B||} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2} \times \sqrt{\sum_{i=1}^{n} (B_i)^2}}$$

A reason why the cosine similarity is one of the most used similarity measures for text documents is that it normalizes document length during comparison. This is very important when comparing text documents since they varies greatly in length.

2.2.6 Classifier Learning (SVD)

Support Vector Machines (SVM) (Cortes & Vapnik, 1995) (Vapnik, 2000) are a group of supervised learning methods that performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. SVM models are closely related to neural networks. In fact, a SVM model using a sigmoid kernel function is equivalent to a two-layer, perception neural network. SVM has been shown to perform very good on a wide variety of classification problems that require large scale input space, such as handwritten character recognition, face detection, and most importantly in this case, text categorization(Dumais, Platt, Heckerman, & Sahami, 1998) (Fukumoto & Suzuki, 2001) (Yang & Liu, 1999)(Jachims, 1998).

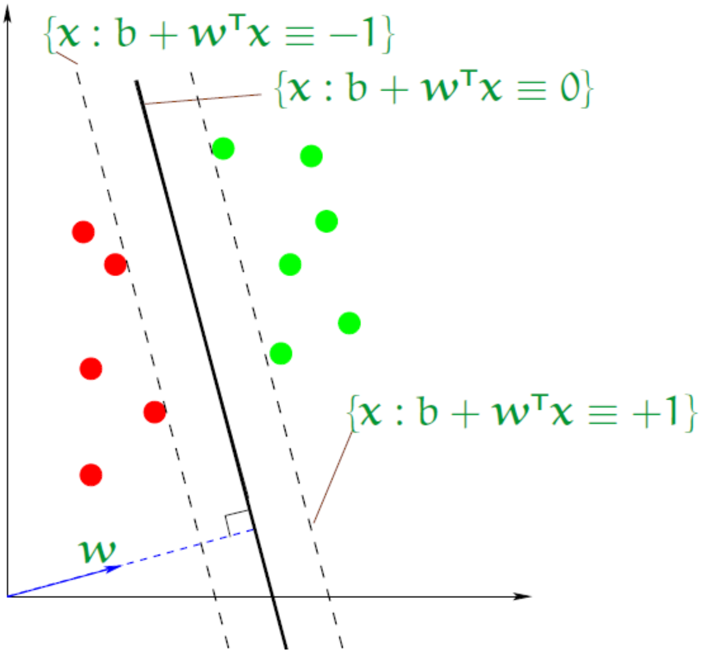

$\{x : b + w^T x \equiv -1\}$
$\{x : b + w^T x \equiv 0\}$
$\{x : b + w^T x \equiv +1\}$
w

FIGURE 2.4: SVM hyperplane and support vectors. Maximum margine.

A SVM constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest data points in the training set (maximum margin). We want to find the maximum margin hyperplane that divides the two classes. The hyperplane can be written as the following equation where x is an arbitrary feature vector and w and b are learned from a training set of linearly separable data.

$$x: b + w^t x=0$$

And the functions for the two support lines for the hyperplane are:

$$x: b + w^t x=+1$$

$$x: b + w^t x=-1$$

The length between the two dotted support lines in FIGURE 2.4 is $\frac{2}{||w||}$. This value should be maximized, and the hyperplane with the largest value is the hyperplane to be chosen. In practice it is much easier to minimize $\frac{1}{2}||w||^2$instead of maximizing $\frac{2}{||w||}$. As we also have to prevent data points from falling into the margin, we add the following constraint: for each data point:

$b + w^t x_i >= +1$ for x_i of the first class

$b + w^t x_i <= -1$ for x_i of the second class

This can be rewritten as:

$Y_i(b+w^t x_i)>=1$ for all $1<=i<=n$

X_i is a feature vector of the ith training document in a training set of n documents and y_i is the class label of the ith training document. All vectors lying on one side of the hyperplane should preferably belong to one class while those on the other side should belong to another. If this is not the case then the optimizing criteria has to be updated from only maximizing the distance between the support lines to adding a penalty for miss-classifications.

To maximize the margin by the given constraint, the following function has to be minimized.

$$Minimizing\ wrt. \propto : \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \propto_i \propto_j y_i y_j x_i^T x_j - \sum_{i=1}^{n} \propto_i$$

$$Subject\ to\ \sum_{i=1}^{m} y_i \propto_i = 0\ and\ that\ \propto_i \geq 0, i = 1, \dots, n$$

This is a quadric programming optimization problem, which is very time consuming. However, it can be broken down into a series of smaller problem by a sequential minimal optimization algorithm which is used for training SVMs.

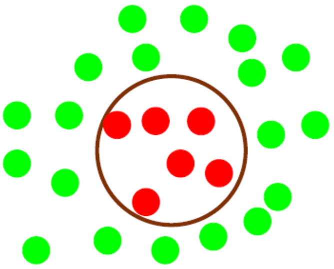


FIGURE 2.5: SVM problem that is not linearly separable

When the problem is stated in a finite dimensional space, it often happens that in that space the sets to be discriminated are not linearly separable, se FIGURE 2.5. This problem is difficult to solve when x=(r,s) has only two dimensions. A solution to this is that the finite-dimensional space are mapped into a much higher-dimensional space, this usually makes the separation easier. For the case in FIGURE 2.5 this could be done by mapping the function into this five dimensional function, $T(X)=\{r,s,rs,r^2,s^2\}$. Doing this makes it possible to find a linear separator for that problem. SVM schemes use a mapping into a larger space so that cross products may be computed easily in terms of the variables in the original space. The cross products in the larger space are defined in terms of a kernel function $K(x_i,x_j)$ selected to suit the problem. A kernel is a similarity measure defined by an implicit mapping ø, from the original space to a vector space such that: $k(x_i,x_j)=ø(x_i)^Tø(x_j)$. The choice of the kernel function is very important for the efficiency of the support vector machine. Some common kernels are:

- Linear Kernel: $k(x_i,x_j)=x_i^tx_j$
- Polynomial kernel: $k(x_i,x_j)=(gamma(x_i^Tx_j)+c)^d$
- Radial basis function (RBF) kernel: $k(x_i,x_j)=exp(-gamma||x_i-x_j||^2)$
- Sigmoid kernel: $k(x_i,x_j)=tanh(gamma(x_i^Tx_j)+c)$

2.2.7 Evaluation Metrics

In the context of classification tasks, the terms *true positives* (TP), *true negatives* (TN), *false positives* (FP) and *false negatives* (FN) are used to compare the class labels assigned to documents by a classifier with the classes the items actually belongs to. *True positives* (TP) are examples that the classifier correctly labeled as belonging to the positive class. *False positive* (FP) are examples which were not labeled by the classifier as belonging to the positive class but should have been. *True negative* (TN) are examples that the classifier correctly labeled as belonging to the negative class. At last there is *false negative* (FN) which are examples which were not labeled by the classifier as belonging to the negative class but should have been. See TABLE 2.5, for a visual aid on how they belong together. Other evaluation measures like precision, recall, F-measure, specificity and accuracy can easily be calculated from these four variables.

		Correct labels	
		Positive	Negative
Classified labels	Positive	TP *(True positive)*	FP *(False positive)*
	Negative	FN *(False negative)*	TN *(True negative)*

TABLE 2.5: Contingency table (TP, TN, FP, FN)

Accuracy

A common measure for classification performance is accuracy, or its complement error rate. Accuracy is the proportion of correctly classified examples to the total number of examples, while error rate uses incorrectly classified instead of correctly. In general, the better the classifier, the higher the accuracy is. However, one should be careful to use only accuracy when one is using skewed data. This is because when one class occurs significantly more than the other, the classifier might get higher accuracy by just labeling all examples as the dominant class then what it gets when it tries to classify some with the other class.

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

Precision and recall

Precision and recall are two widely used metrics for evaluating performance in text mining, and in other text analysis field like information retrieval. They can be seen as extended versions of accuracy, and by using a combination of these measures the problem with skewed data for classifiers dissipates.

Precision can be seen as a measure of exactness, whereas recall is a measure of completeness. In other words, a high precision means that the most of the documents labeled as positive are labeled correctly (but it might not have found many of the positive documents) and a high recall means that it has found most of the positive documents (but it might also have labeled many negative documents as positive). The higher the precision gets, the lower the recall becomes, and the higher the recall is the lower the precision is.

Precision is the number of examples correctly labeled as positive divided on the total number that are classified as positive, while recall is the number of examples correctly labeled as positive divided on the total number of examples that truly are positive. This is shown in the following formulas.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

F-Measure

F-Measure is the harmonic mean of precision and recall. This gives a score that is a balance between precision and recall. Precision and recall captures two different, but important, aspects of the classifiers performance, and the F-Measure combines them into one score for easier usage. In this thesis the F_β-measure is used because it can use its beta parameter to weight the importance of precision and recall differently. This is important because it might be better to optimize the system to favor either the precision or the recall if one of these has a more positive influence on the final result of the trading simulation than the other.

$$F_\beta = (1 + \beta^2) \times \frac{Precision \times Recall}{\beta^2 \times Precision + Recall}$$

3 Related Work on News-Stock Relationship Systems

While there is a multitude of published articles about data mining, time series and other techniques in prediction of stock prices, the numbers of articles covering the application of text mining in stock market predictions are few. The reason for this is that this is still a new field. Some of the earlier works that started to use textual news articles for financial forecasting is from 1998 (B, et al., 1998) and 2000 (Lavrenko, Schmill, Lawrie, Ogilvie, Jensen, & Allan, 2000). The systems described in this section is however of more recent dates.

3.1 Outline of Related Methods

The general structure of the earlier published related works has many similarities between them. All of those reviewed in this thesis are build around a central learning algorithm (mostly a classifier) for predicting the sentiment (price direction) of news articles. And for the learning algorithm to work it needs a training set. The generating of those training sets is done in many different ways so they are described in a separate section. A set of features has to be extracted from each news document for the learning algorithm to be able to work on them. Different systems do this in different ways, and since this is a vital part, it is described in its own section. At the end the architectural structure of these different systems is described in more detail.

3.2 Training Set Creation

Most of the sentiment categorization methods involves a classifier that needs to be trained on a set of pre sentiment labeled documents or with a vocabulary of sentiment labeled features (words) to be able to correctly categories new news articles. Training sets can either be generated manually by experts (Xun & Chen, 2005), or they can be generated automatically by the system. The automatic sentiment categorization approaches are of most interest for this project since the manually based methods are more time consuming and requires expert knowledge on the given domain to be sure that it is correct.

The NewsCATS engine (Mittermayer, 2004) categorizes news articles into a training set with these three categories, “Good news”, Bad news”, and “No movers”. They categorize articles as “Good news” if the stock price relevant to the given article has increased with a peek of at least +3% from its original value at the publication time at some point during the 60 minutes that follows. The average price level in this period has to be at least 1% above the price at publication. For “Bad news” the opposite is true, the movements have to be in the negative direction instead. The rest of the articles in between are classified as “No movers”.

The AZFinText system (Schumaker & Chen, 2010), is a regression system that tries to predict feature prices and it is not a true sentiment classifier. This means that this system labels each news article with a price value instead of sentiment label. The AZFinText system does this by labeling each news article with the stock price 20 minutes after it is published.

The system developed by Pegah Falinouss in his master thesis (Falinouss, 2007) uses some time series segmentation techniques to find price trends by reducing the noise in the price curve. FIGURE 3.1 shows a segmented time series and how news articles are linked to it by the time they are published. He talks about two different method of labeling the news articles. Method one is “observed time lag”, which has a time lag between publishing time and when the public absorbs and act on it. This means that group X in FIGURE 3.1 is responsible for trend B. he has used this kind of labeling. The second method, which Falinouss has chosen to use, is build on the efficient market theory, which state that there is no time lag between publishing time and market correction for this piece of information. This means that news article group X in FIGURE 3.1 is responsible for trend A and group Y for trend B.

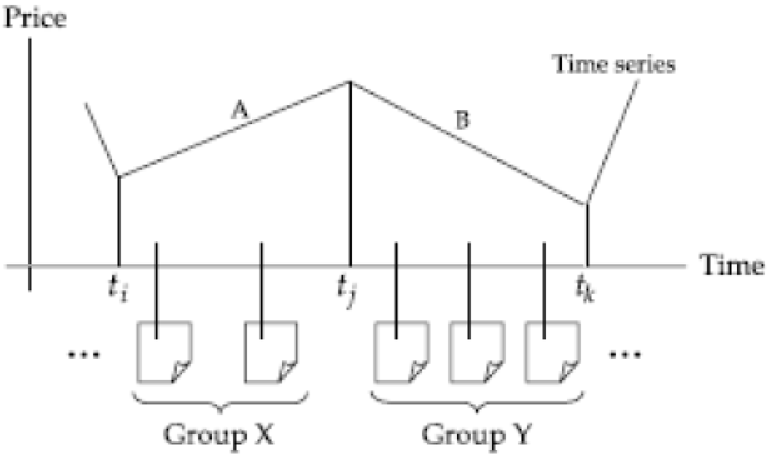


FIGURE 3.1: Trend, news alignment methods

The system created by Fook Hwa Tan in his master thesis (Tan) describes two labeling methods; (I) labeling by trading volume and (II) labeling by returns. Labeling by using the volume labels news articles into two classes, high volume and low volume. The division is controlled by whether the given volume is above or below the average trading volume or above/below the average trading volume plus/minus the standard deviation over the whole period. A classifier trained by this method can only predict whether a news article will initiate a high number of trades or not, it cannot predict the direction of the price movement. Labeling by returns looks for abnormal return amounts and label news articles from that. Abnormal is the actual return minus the expected return, which is calculated in the following manner:

Abnormal return = actual return – (α+ β* return on the market index)
Actual return = return from the given stock
Return on the market index = Return from the entire stock market

Where α show how much on average the stock price changed when the market index was unchanged, and β tells us how much extra the asset price moved for each 1 percent change in the market index. The abnormal return values is then used to label news articles as rise, plunge or not relevant. A parameter called gamma is used to control how far above or below zero the abnormal return has to be for the news article to be labeled as rise or plunge and not as not relevant. Tan uses a one day interval to calculate the return values (selling price – buying price) for finding the abnormal returns value. However, he chose this interval because he did not have access to intraday data, and he refers to studies stating that shorter intraday intervals give better results.

3.3 Document Representation

The vector space model together with the tf-idf feature weighting method (see section 2.2.5) is the most common approach among the different systems for representing the news articles. However there are many different methods for extracting and selecting the features used in these vector space models.

The NewsCAT engine (Mittermayer, 2004) is one of the methods which use a vector space model with a tf-idf feature weighting scheme. It uses single words, or unigrams as features, but it only selects n features with the highest tf-idf score to represent the news article.

Schumaker and Chen (Schumaker & Chen, 2006) examined the role of financial news articles on three different textual representations; Bag of Words, Noun Phrases, and Named Entities and their ability to predict discrete number stock prices twenty minutes after an article release, which is a regression problem and not a categorization problem. They demonstrate that using a Named Entities representation scheme performs better than the de facto standard of Bag of Words on their Support Vector Regression (SVR) prediction engine.

Bag of Words	Noun Phrases	Name Enteties
Fined	Reuters	Reuters
Fourth quarter	NYSE	Fourth quarter
The NYSE	Fourth quarter	Schwab
Schwab	Profit	
Profit	Schwab	
fell		

TABLE 3.1 Feature types from (Schumaker & Chen, 2006)

The bag of words technique is the standard way of representing a text document and it is simply a collection of the words believed to best represent the document. Noun phrases (NP) is a phrase normally consisting of a head noun, which is often together with a modifier set (e.g. *the red ball*, or *a ball*). Name entities (NE) are words and phrases describing things like names of persons, organizations, locations, expressions of times, quantities, monetary values, percentages, etc. Name entities are a more specific and concrete form of noun phrases. Some examples of features extracted from a text by these three different methods can be seen in TABLE 3.1.

Simulated trading	Regression	Model
Bag of Words	-$1,809	$5,111
Noun Phrases	-$1,809	$6,353
Name Enteties	-$1,879	$3,893

TABLE 3.2: Return from Simulated trading (Schumaker & Chen, 2006)

Outlay	Model
Bag of Words	$228,000
Noun Phrases	$295,000
Name Enteties	$108,000

TABLE 3.4: Money invested (Schumaker & Chen, 2006)

Percentage return	Model
Bag of Words	2.24%
Noun Phrases	2.15%
Name Enteties	3.60%

TABLE 3.3: Percentage return on money invested (Schumaker & Chen, 2006)

The trading method invested $1,000 per new trade, and TABLE 3.2 shows how much each of the different trading methods gave in return after a fixed trading period. Noun phrases gave the biggest return from the simulated trading run with a return of $6,353, next was bags of word with $5,111 and name entities had the lowest return with $3,893. However, TABLE 3.4 shows that noun phrases and bags of words invested much more money in total, which means they performed many more trades since each trade only invested $1,000. If the amount of money invested is taken into consideration it shows that the name entities method gives a much higher percentage return on the money invested than what the two other methods does, this can be seen in TABLE 3.3. This means that the two other methods predicted wrong many times more than what the name entity method did.

The AZFinText model (Schumaker & Chen, 2010) extracts proper nouns and selects the proper nouns that occurs three or more times to be used as features. They are the same people that did the above study where they concluded that of the three feature types; bag of words, noun phrases and name entities, the name entity feature type gave the best results. However in this system they chose to use proper nouns (not included in their previous study), which is a subset of the set of noun phrases and a super set of the name entity set, which means it lies in between those two sets.

3.4 Architectures of News Based Trade Support Systems

This section describes the system architecture and shows some of the results of a few different systems. Parts of them are described in the above sections. Most of them, in addition to analyzing news articles, also have added a trading engine and shows the result from some simulated trades.

3.4.1 NewsCAT

The NewsCAT method (Mittermayer, 2004) tries to predict price trends (incline, decline or flat) immediately after press release publications. This system consists mainly of three components, and how they are connected in a system can be seen in FIGURE 3.2: NewsCATarchitecture. The sentiment labeling news articles that are used as a training set for train the NewsCAT classifier is described in a paragraph under section 3.2.

Text preprocessing engine: This component retrieves relevant information from press releases and transfers them through a preprocessing stage consisting of tokenization, stop-word removal and stemming. Features are then selected from the n number of words with the highest tf-idf score.

News Categorization engine: This component sorts each press releases into predefined categories, “Good News”, “Bad News” or “No Movers”. NewsCAT uses support vector machine (SVM) as its classification algorithm.

Trading strategy engine: This component derives appropriate trading strategies for when to buy, sell and hold by the use of the output from the categorization engine.

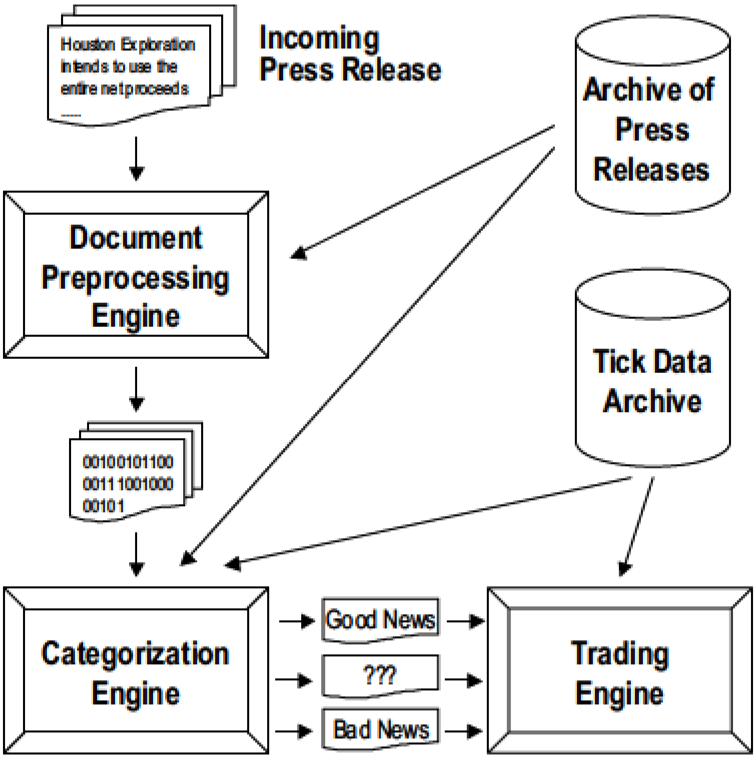
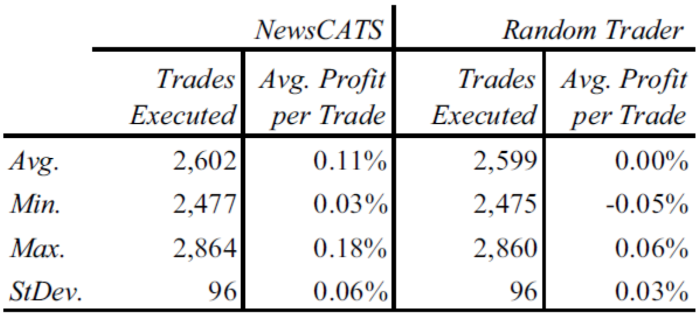


FIGURE 3.2: NewsCATarchitecture



	NewsCATS		*Random Trader*	
	Trades Executed	*Avg. Profit per Trade*	*Trades Executed*	*Avg. Profit per Trade*
Avg.	2,602	0.11%	2,599	0.00%
Min.	2,477	0.03%	2,475	-0.05%
Max.	2,864	0.18%	2,860	0.06%
StDev.	96	0.06%	96	0.03%

FIGURE 3.3: NewsCAT vs random - trade profit

The selection of no movers by the NewsCAT system is reported to be fairly good, while the selection of “good news” and “bad news” is fairly bad. They believe the reason for this is that the words used in “no movers” documents and for “movers” documents probably are very different while the words in “good news” and “bad news” documents might be more similar (e.g. only the word “not” might spate a good and a bad article in some cases). The system is reported to significantly outperform a trader randomly buying and shorting stocks immediately after press releases, which can be seen in FIGURE 3.3: NewsCAT vs random - trade profit. Ass seen the system has an average profit of 0.11% per trade while the random trader has zero profit. By using a different trading strategy which used some support lines as barriers to lessen some of the risk they managed to get a 0.21% profit per trade while the random trader only got 0.07% with the same strategy.

3.4.2 AZFinText

The Arizona Financial Text System (AZFinText) (Schumaker & Chen, 2010) is another machine learning system that uses financial news articles and stock quotes as its input to predict feature stock price movements. As mentioned earlier in section 3.3, this system uses proper nouns as features, and selects the proper nouns that occurs three or more times to be included in the feature set. It distinguishes itself by using a support vector regression (SVR) algorithm instead of a classification method as most of the other system are using. This means that it tries to predict a feature price value when given an article; more precisely it uses the article to predict what the price will be in 20 minutes. While the other methods mentioned in this thesis only categorizing the news as good, bad or neutral. AZFinText have implemented a trading engine that buy or short a stock if the predicted price movement is greater or equal to 1%, and any stock bought or shorted are then liquidated after 20 minutes. FIGURE 3.4: AZFinText architecture illustrates how the AZFinText system is designed.

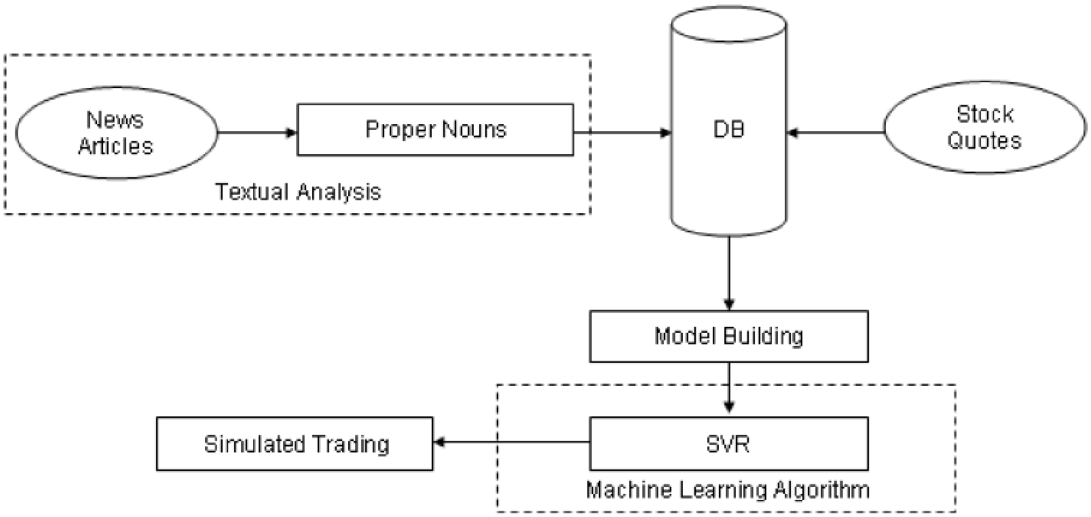


FIGURE 3.4: AZFinText architecture

The AZFinText system was tested on S&P 500 and compared against the top quantitative funds[32]. It had an 8.5% return in the given period, while the S&P 500 had a lesser return of 5.62%. It ranked as number four against all the other quant funds. However, those quant funds that ranked above it traded in different markets than the AZFinText system. When ranked against other quant funds trading only in S&P 500 then AZFinText system performed better than the rest of them, as seen in TABLE 3.5.

	Return
AZFinText	8,50%
Vanguard Growth & Income (VQNPX)	6.44%
BlackRock Investment Trust Portfolio Inv A (CEIAX)	5.48%
RiverSource Disciplined Equity Found (ALEIX)	4.69%

TABLE 3.5 AZFinText vs quant founds

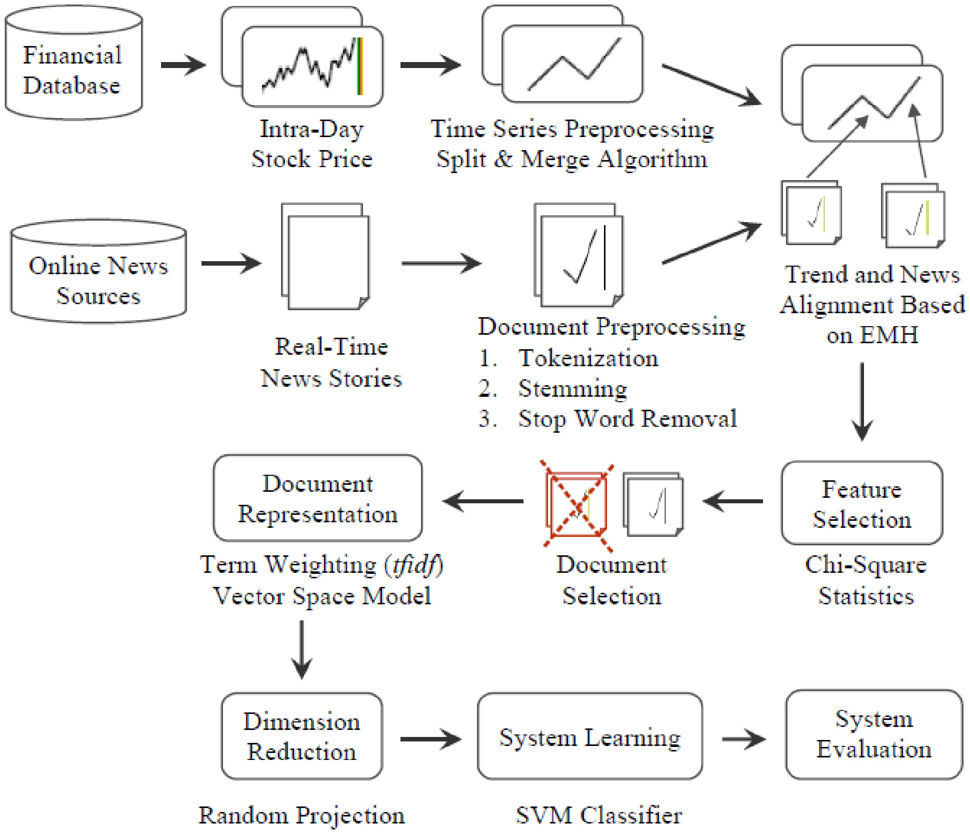
The AZfinText system has also been used together with two basic quantitative portfolio selection strategies in an attempt to increase the performance of the system. The two quantitative portfolio selection techniques used was a *Momentum strategy* and a *Contrarian strategy*. The hybrid system with the use of the Momentum strategy with a 1-week portfolio formation period archived 20.79% in trading return, which is much better than the 8.50% that the AZFinText system had alone. In

[32] A quantitative fund or quant is an investment fund in which investment decisions are determined by numerical methods rather than by human judgment. (Dempester, Gautam, & Pflug)(Quantitative fund: Wikipedia)

combination with the Contrarian strategy over a five-week holding period, the system had a 4.54% trading return.

3.4.3 Falinouss

The main parts of the system developed by Pegah Falinouss in his master thesis (Falinouss, 2007) can be seen in figure x. These steps consists of finding price trends by time series segmentation, then each news document are sentiment labeled by aligning them up with the price trend. The document preprocessing part consists of the three standard methods; tokenizing, stop-word removal and stemming. Then the documents for the training set are selected by going thru a process called document selection. This process calculates the chi-square value for each feature and only selects documents with minimum one significant feature. After that the document representation is done by the standard method of using a vector space model with tf-idf as the term weighting method. This system also includes a feature reduction process which is done by the random projection (Bingham & Mannila, 2001) method. And at last the SVM classifier is used for classifying the sentiment of news articles as rise or drop.



This system is reported by Falinouss to have an accuracy of 83% for correctly labeling a news article as rise or drop. The recall of rise predictions are stated to be 67%, and for drop predictions it is 93%. The precision for rise predictions are claimed to be 87% and for drop 81%. Falinouss did not include an evaluation part on how good this system is when used for trading stocks.

4 Scientific Approach

In the previous chapters a variety of methods used for news based trading systems have been reviewed. Based on this theory, an automatic news based trading decision support system was developed. This chapter provides a description of the implemented system.

4.1 Approach Overview

The approach adopted in this thesis is based on classification of published news articles as being positive, neutral or negative. If a news article is positive it means that it is likely to be followed by an upward moving price trend for the specific stock, if it is neutral the price trend is likely to be flat, and if negative the price trend is likely to fall. Then a trading decision maker uses this information about the news article to make a trading decision regarding the stocks of the related company.

The implemented system consists of a number of main concepts. First, the time stamped news articles and stock prices needs to be acquired from internet during a data acquisition process. Then these news articles have to be labeled so they can be used in training and testing the classifier. This entire process is shown in FIGURE 4.1. The top part of the figure shows the component involved in data acquisition, which is described in detail in section 4.2. Next it is the news labeling component which labels news automatically by using stock prices, it is described in section 4.3. The next component in FIGURE 4.1 is the document preparation process, which is described in section 4.4. In it, each news article goes through a process that consists of a document preprocessing part, a document elimination part, and a document representation part. Then the documents are entered into a label refining process in an attempt to improve the correctness of their labels; this component is described in section 4.5. The labeled news articles are then used for training and testing of the classifier. The last component in the figure is the trading process, it takes news articles labeled by the trained classifier as input and simulates stock trades based on what type of label it is. The classifier and the trade engine are described in section 4.6 and 4.7. Not all the steps in FIGURE 4.1 are required. Some are optional and others have multiple choices. Some of the optional ones are stop-word removal and stemming, and some of those with multiple choices are label refining and feature reduction.

The programming language Python was used to do all the programming for this system. Some packages (libraries) were used for the development, the main ones being *natural language toolkit* (NLTK) and *SVMLIB* with its Python interface.

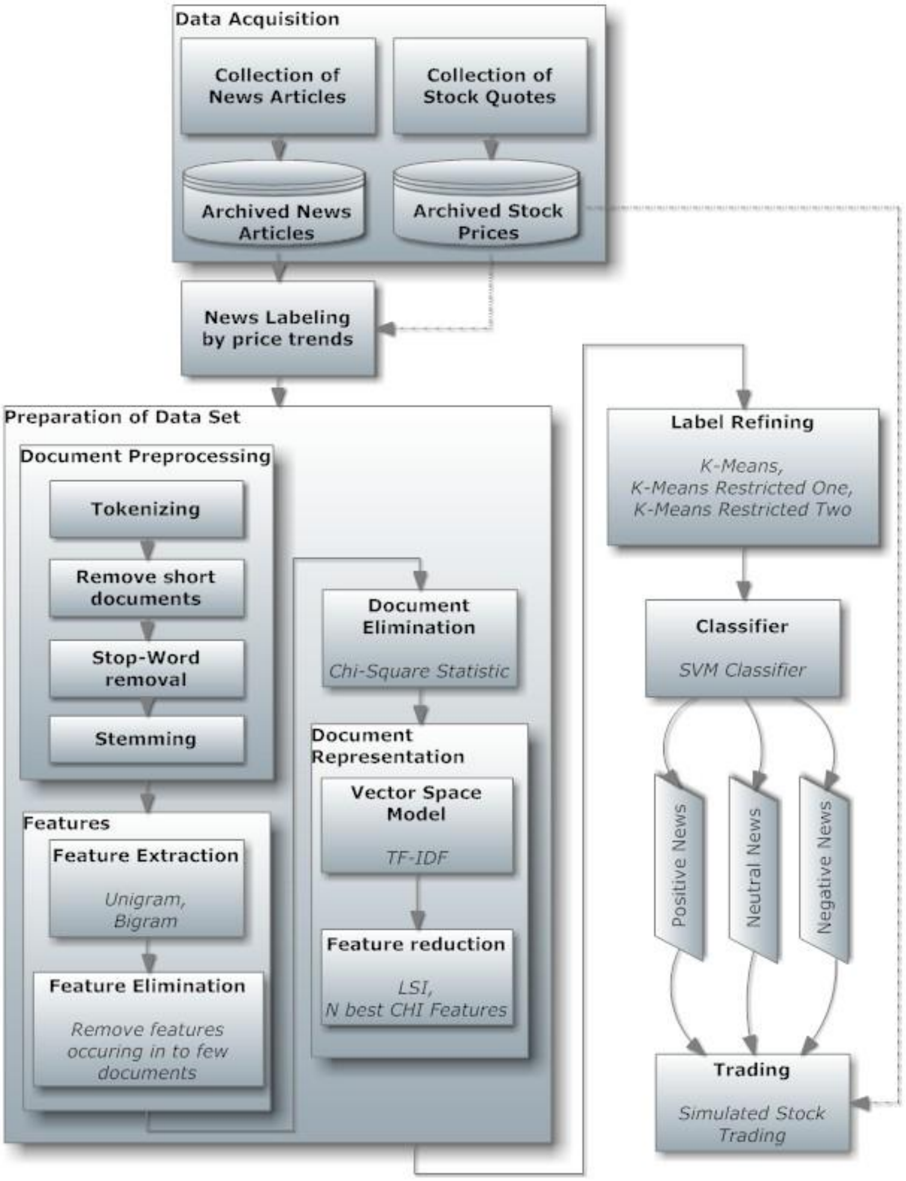


FIGURE 4.1: The workflow of our proposed automatic news based trading approach

4.2 Data Acquisition

For this project two types of data are required; (I) time stamped news articles and (II) stock prices. This data acquisition step is performed at the beginning, and can be seen in FIGURE 4.1. The following sections describe how these two types of data are gathered.

4.2.1 Collection of News Articles

The news articles that are gathered will be labeled as positive, neutral or negative. The labeling techniques that are used to label the news articles are doing it by using stock prices. This means that the news articles that are to be gathered must be time stamped so they can be linked to stock prices. The web page Netfonds gathers time stamped news articles from various financial news sites and groups them together according to the companies they belong to. This means that in addition to fulfilling the requirement of having time stamped news articles, this site also removes the need to make a categorization engine to group news articles together with companies they belong to. Three of the financial news sites that Netfonds collect news from are; Hegnar online, Newsweb, and Thomson Reuters ONE.

A web crawler is created which takes a starting date, days to look back, and one or multiple tickers as parameters. Then it crawls the site to look for news articles fitting these parameters. Each news article is stored in a text file under the folder named after the company it belongs to. The naming convention of the text file is like this: “date time company-ticker news-source title.txt”. The news articles information is stored inside the text file with additional information and in a structured way that makes it easier to be reused later on:

```
<doc>
<date></date>
<time></time>
<source_link></source_link>
<source></source>
<text>
<title></title>
<body></body>
</text>
</doc>
```

Some of the news sources publish articles in both Norwegian and English without giving any kind of identifier to separate the two languages. This raised the need to create a language classifier. Since this would only be used to separate two languages this is done by creating a set of high frequency words for each language and labels each news article with the language it had most words in common with. This process is a part of the news article collection component FIGURE 4.1; it is not shown in the figure.

4.2.2 Collection of Stock Quotes

Stock prices are collected about companies in Oslo Stock Exchange (OSE), and both intraday and daily stock quotes are gathered. Intraday trade information was provided by one of the project supervisors, Arvid Holme. A program is also written for gathering daily quotes from the web page Netfonds, which has daily quotes as far back as 2001 on some companies. Intraday quotes consists of date, time, price and volume information for each trade, while daily quotes consists of date, time, open price, high, price low price, close price, and trading volume for that day.

4.3 News Sentiment Labeling by Price Trends

This method creates a training set of news articles for the news sentiment classifier by automatically labeling each news article with a sentiment. This is done by looking at how the price trends move after the news articles are published. If the price trend is up, then the news is labeled as positive, if the trend is down, then it is negative, and when the trend is flat it is labeled as neutral. This can be done on both intraday and daily prices. A couple of different methods to do this labeling are developed, but the main idea behind each is the same. After this process is finished, each news article is labeled as positive (uptrend), neutral (flat), or negative (downtrend). This step, as seen in FIGURE 4.1, is done after the data acquisition step and before the document preparation. The reason why this step is performed before any news article documents are prepared is that this step only needs the news article id, publication date and time, and stock prices, and not the content of the news.

4.3.1 News Trend Labeling: Method One

The first method is similar to the method used by NewsCAT (Mittermayer, 2004). It finds the average price for a given period following directly after the publication of the news article, If this value has changed more than a given percentage α from the price at publication, and if a maximum price in the price trend direction has been above a given percentage β than the start value, then the article is classified as either positive or negative based on the direction of the price trend after publication. If this is not the case, then it classified as neutral. This process is shown in FIGURE 4.2, and can be easier to understand by looking at the following algorithm.

$$avg = \frac{avgPrice - pubPrice}{pubPrice}$$
$$max = \frac{maxPrice - pubPrice}{pubPrice}$$
$$min = \frac{minPrice - pubPrice}{pubPrice}$$

$$IF\ avg > \alpha\ AND\ max > \beta\ THEN\ news = positive$$
$$IF\ avg < -\alpha\ AND\ max < -\beta\ THEN\ news = negative$$
$$Else\ news = positive$$

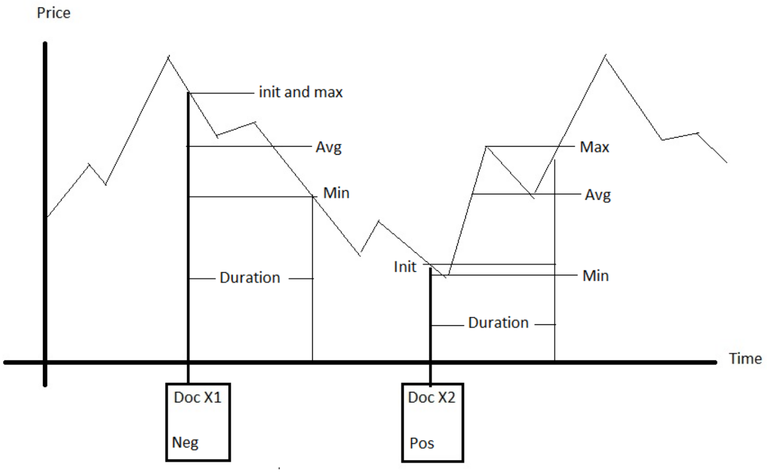


FIGURE 4.2: News labeling from price trends method one - from NewsCAT

4.3.2 News Trend Labeling: Method Two

The second method finds the straight line that best fits the price values in a given period after the publication by using the least square method. It then calculates the slope of this line, and if it is larger than a given threshold value the news article is classified as positive or negative, depending on the direction of the slope. If the slope does not cross this threshold value, then it is classified as neutral. This method has been used only in the very early experiments, and is not used in the experiments performed in chapter 6. The slope for the regression line is found according to the following formula:

$$slope = \frac{\sum x * y - \frac{\sum x \sum y}{n}}{\sum x^2 - \frac{(\sum x)^2}{n}}$$

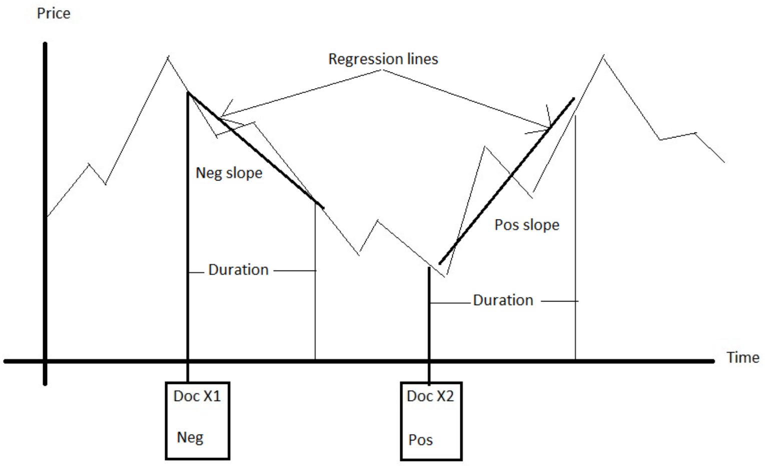


FIGURE 4.3: NEWS LABELING FROM PRICE THRENDS METHOD Two

4.3.3 Combining different labeled data sets

One method that might increase the correctness of the labeled data set is to combine two different data sets labeled by the first or the second methods to a single set. The two training sets are generated with different parameter setting, and one should use a longer trend duration while the other should use a shorter one. This will ensure that the two data sets are not identical. The new data set should consist only of documents that are labeled with the same sentiment in both of the other sets. This reduces the total number of documents in the data set, but the sentiment label should, in theory, be more likely to be correct.

4.3.4 Price trend timing

As mentioned above, labeling is done by using the price trend after the article is published. Most of the related research that uses an automatically labeled training set uses stock price trends in their labeling techniques. However, how to decide when this trend starts in relation to the time the news article is publishes varies greatly between the different approaches. The start points of the trend is, as seen later in the experiments in chapter 6, important for the labeling method to produce more correct labels, at least when daily prices are used. The reason for this is that daily price data only operates with two timed values, opening and closing prices. This means that the price trend might have been started long before or after the time the news article was published. This means that the market might already have adjusted to the news before the trend calculation started if it is started after the news is published. If it is started before, it might be that the trend is in response to some other piece of information and not the given news article. Of course, this last problem is also likely to give some false labels when there is multiple news articles published in one day for a given company, which is often the case for the more popular companies. The methods described in label refining in section 4.5 will hopefully reduce the impact of this problem thereby removing some of the noise in training sets that comes from it.

The price trends belonging to each news article are found in two slightly different ways when daily prices are used. The only difference between the two methods is when they start to calculate the trend. They give quite different outcomes, as seen later in the experiment one; hence it is important to choose the right one.

Method one: It starts the trend from the price right before the article is published. This means that the articles published before the stock exchange has opened starts its trend calculation from the previous day's closing price. Articles that are published during the opening time starts with the opening price of that day and articles published after it has closed start with that day`s closing price.

Method two: This method starts with the price immediately after the publishing time. That means that articles published before the stock exchange open starts its trend calculation from this day`s opening price. Articles that are published during the opening time starts with the closing price of that day and articles published after it has closed start with the next day`s opening price.

When labeling is done with daily price data only, the news articles published on trading days are used, the rest of them are excluded. This is also true when labeling is done with intraday prices. However, when intraday prices are used, then all news articles published outside of the stock exchange`s opening time, or to close to the end of the opening time to calculate a price trend, is also removed. Intraday labeling follows the general idea of method two for trend timing; however, it looks only at the publication day and not over multiple days.

4.3.5 Manually Labeled Set

A collection of manually sentiment labeled documents is created. These labels are not decided by a financial expert, so there might be some small errors in them. However, many news articles have a clear positive or negative spin to them that non experts can identify. This manually labeled set of news document set is primarily going to be used for evaluation, but it can also be used as seeds to create a training set with a seed based approach, which are a semi-unsupervised clustering method. However, this is not done in this thesis.

The manual labeling is done purely by reading some news articles and labeling. No stock price data is taken into consideration when labeling, only the information given in the news article.

The manually labeled training set consists only of positive and negative documents. This means that when the automatically created sets are compared with the manually labeled, they are only evaluation how similar the positive and negative documents found by the automatic method are to the manual set. The documents that are labeled as neutral are not evaluated.

4.4 Preparation of Data Set

After the news articles have been gathered they have to be prepared before they can be categorized. This process can be seen in FIGURE 4.1. The steps in this process are; (I) document preprocessing, (II) Features extraction and selection, (III) document elimination and (IV) document representation. The prepared data sets will be used for training and testing of the classifier.

4.4.1 Document Preprocessing

The document preprocessing step consists of the four steps, tokenization, short document removal, stemming, and stop word removal. Some of them are described in section 2.2.1. These steps can also be seen in FIGURE 4.1 under document preprocessing.

Tokenizing: is done by first processing the text with the wordpunct tokenizer in the python library “Natural Language Toolkit” (*nltk*), which is one of several tokenizers in that particular library. It works by dividing the text into tokens by separating it on whitespaces and on signs like comma, punctuation and explanation signs. After that all signs are removed so only words and numbers are left as tokens.

Short doc removal: The short document removal process removes short documents, just as the name indicates. The minimum length of the remaining documents is given by an input parameter for this function. This documents that are to short are removed.

Stop-word removal: Method one for stop-word removal method one uses a Norwegian stop-word list which is inside the *nltk* package, but this list include some potentially important words like “ned” (down) and “opp” (up), so a second method is added which only removes words of two characters or less. This last method is used on the experiments done on the final system.

Stemming: The stemming process uses a snowball based stemmer for the Norwegian language, which is also included in the nltk package.

4.4.2 Features

At this stage the news documents has been preprocessed and is now ready for the feature extraction process. These features that are extracted are later used when the documents are represented. This stage also has a feature elimination step to remove some features that are likely to be of little importance.

Feature Extraction

This process extract features from the news documents. Two types of features can be extracted; unigrams and bigrams. These feature types are described in greater detail in section 2.2.2. These two feature types are compared against each other in section 5.5, and bigrams are chosen to be used for the experiments in chapter 6. The features that are extracted are placed in an inverted index.

Feature 1 → {(doc id, frequency, term weight), (doc id, frequency, term weight)}
Feature 2 → {(doc id, frequency, term weight)}

At this point only doc id and frequency is added. The term weight is added later in the document representation part. The news articles are now on good way to their finished representation. However, the last steps in this process come later under the document representation part.

Feature Elimination

This part simply eliminates features that occur in less than a given number of documents. The reason why these features are removed is that they are very unlikely to be of any help for classifying since they occur so seldom.

4.4.3 Document Elimination

After each news article has been labeled we need to eliminate documents that are not at any use for the classifier. Not every document is useful for prediction, in reality many documents are useless for this purpose and thus only contributes as noise. Only documents that contains at least one significant feature for distinguishing between the three categories; positive, neutral and negative are kept. Those documents that do not include any significant features are removed because they are of no use for training the classifier. The feature selection method chosen in this thesis is the chi-square method, se section 2.2.2 for explanation.

4.4.4 Document Representation

The vector space model is used as document representation. More general information on document representation can be found in section 2.2.5. Each document is represented by a vector of numeric values where each value indicates the importance of the feature connected to it. These values are calculated by the chosen term weighting method, which in this case is the tf-idf method (see section 2.2.5 for explanation). When the document representation vector is created, features that are not in the given document will be given value zero. This means that each document vector has the same n-dimensions, where n is the number of selected features.

Term weighting: The feature weighting method that is chosen is the popular *tf-idf* method, which is described in section 2.2.5. The *tf-idf* method is very popular and generally gives good results while still being quite efficient.

Dimensionality reduction: The *SVD* method, which is described in section 2.2.4, is chosen to perform the feature reduction. The *SVD* method is well known and gives good results, but it is slow and demands huge amounts of memory. This is not a problem for this thesis, but for a real time news-trading assistant product, another faster and less memory demanding approach is better suited (e.g. random indexing). A second feature reduction technique is also implemented. It simply find the chi-square values for each feature and either pick top n features or pick all features with a value above a given threshold value. This method might more correctly be named feature selection and not feature reduction. The SVD method is used in most of the experiments.

4.5 Label refining

After each news article is sentiment labeled by the basic method of using price trend directions, and after all the documents have been prepared and given a document representation, a label refining step is added in an attempt to improve the labels given to the news articles. The reason why this is done is that the basic labeling method is very likely to result in a labeled data set with a significant degree of noise. If daily price data is used, then all articles published in the same day is given the same sentiment, but some of them are likely to be neutral, if not the opposite sentiment. It still will be noise, even when intraday price data is used because the news article sentiment will not always correlate with the same price trend.

The documents given to this method is labeled by the basic labeling method with positive, neutral, or negative labels. If we assume that a document with a given label has more in common with other documents of the same labels than it has with documents with different labels. And we assume that the basic labeling method gives more correctly labeled news articles than falsely labeled ones. Then one possible way to fix this noise problem is to use some kind of clustering method to rearrange the documents in these three groups of labeled documents. This should work if the assumptions are correct because then the three groups of positive, neutral and negative documents is in fact three clusters.

By adding this technique of label refining the classifier performance should be better when it is tested on the automatically labeled training set. This is because the three groups has become easier to distinguish because of the clustering process, thus it becomes easier to train a good classifier. However, the labels might still be noisy with many incorrect labeled news articles. The reason for this is that not every document that is close to a group of documents with one label is necessarily of the same label as them. However, the clustering methods will give them the same label as its closest neighbors, even if that is an incorrect label.

4.5.1 K-Means clustering

The k-means algorithm is one of the simplest unsupervised learning algorithms that are used for clustering documents, or data. It clusters the data in k clusters, and it does it by executing the following steps.

K-Means algorithm:

1. Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.
3. When all objects have been assigned, recalculate the positions of the K centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

In this problem, where the sentiment labels found by labeling the news articles from the price trend direction have to improve, the initial k centroids are from the three groups of documents that are labeled as positive, neutral, and negative. The closeness in step two is measured by the cosine similarity between the documents and the cluster centroids, which are described in chapter 2.2.5.

This method is very likely to be clustering the document labels to much, thus it will likely have a high noise factor because of many incorrectly labeled news documents. This means that the classifier should perform very well when tested on the automatically generated data set, but it is not very likely to perform that good when it is compared with the manually labeled data set. Because of this, a couple of other method based on K-Means, but with some restrictions where implemented.

4.5.2 Restricted k-Means clustering method one

A refining method based on the K-Means clustering algorithm used above only with some added restrictions is also created. These restrictions deny the clustering method to directly move documents from positive to negative, and vice versa. If a document is told to do one of these moves, then it is instead moved to the neutral cluster. However, the next clustering round, when the cluster centroids has been updated, it is allowed to be moved to any location since there are no restrictions when moving from the neutral cluster. The extra rules are like this:

1. Document from positive to negative: Not allowed, move to neutral.
2. Document from negative to positive: Not allowed, move to neutral
3. Document from negative or positive to neutral: Allowed, move document to neutral
4. Document from neutral to any other cluster: Allowed, move document
5. Document from cluster x to cluster x: Allowed, keep document at same position

By adding these extra rules there are less documents that are moved from positive to negative and negative to positive. This means that there should be less chance that the documents in the positive and the negative clusters changes so much that these clusters no longer represents positive and negative documents.

4.5.3 Restricted k-Means clustering method two

A second restricted method that is also based on the K-Means algorithm is also added. These restrictions deny the clustering method to move documents from positive to negative, and vice versa. If a document is told to do one of these moves, then it is instead dropped from the document collection.

6. Document from positive to negative: Not allowed, remove document.
7. Document from negative to positive: Not allowed, remove document
8. Document from negative or positive to neutral: Allowed, move document to neutral
9. Document from cluster x to cluster x: Allowed, keep document at same position

This method will in most circumstances end up with a smaller news collection after it has finished than it had before it began. However, it should lessen the likelihood even more that clusters rearrange so much that they no longer represent positive, neutral and negative news documents, which might be able to happen with the above method.

4.6 Classifier Learning

The classifier method used for the learning algorithm is the Support Vector Machine classifier (SVM). It is used to find the sentiments of any given news articles, or more precisely, the relationship between the contents of news stories and price trends. The LIBSVM library together with the included python interface is used for implementation of the SVM algorithm. Among the possible kernels for the SVM classifier (discussed in section 2.2.6), the RBF kernel which have proven to be best suited for text classification is chosen. To be precise, the RBF kernel and the polynomial kernel have both proven to perform best in different studier. However the RBF kernel is faster, and is therefore chosen instead of the polynomial kernel. The RBF kernel requires two parameters to be set, cost and gamma. The details on how these two parameters are chosen are described in section 5.6.

After each document has undergone the steps required to produce their document representation and been labeled with a sentiment label they are randomly divided into two sets, a training set and a test set. Typically the division is; 70 percent of the documents in the training set and the remaining 30 percent in the test set. The training set is used to train the classifier, while the test set together with a manually labeled set are used to evaluate the performance of the system.

4.7 Trading Engine

The trading engine implements a straight forward and simple trading strategy, it is told by a decision method whether to buy, sell (short selling) or do nothing. Then after a fixed duration of time it liquidates the assets it bought or shorted. This is not a good strategy since the assets that are obtained can experience huge losses and still nothing is done about it until the fixed time duration is finished. However, this is not that important in this study because this weakness is the same for both the news article based trader and the random walk trader, and it`s the comparison between them that`s of interest. If one of them gives better results than the other with this method then it stands to reason that it also performs better when companied by a better trading strategy.

There are three different decision methods for deciding what signal, buy, sell or hold, that are used by the trade engine. These three methods are:

News article trading: This method decides its trading signal by analyzing news articles and deciding what to do from the result of the analysis.

Random trading: This is basically a random trader. Buy, sell and hold signals are randomly generated. The profit from this should overtime be on average zero, but it is still implemented since it is easily done.

Buy and hold: This is method only buys and then holds the stock. In this setting it means that the trade engine always is given a buy signal, and then after the fixed time duration it sells what it has bought.

For simplification purposes the trading engine assumes that each trade is done with the same amount of money, it therefore returns a percentage value to show how much it has returned. In this way it is possible to just multiply it with the chosen amount of money to be used on each trade to find how much it earns or losses. This is not the most realistic way of doing it since each trade seldom consists of the same amount of money, but it gives a good indication of how the trading strategy does and for the purpose of this article it is more than good enough.

5 Experiment Preparation

Before the main experiments can be performed some system parameters has to be chosen. This chapter describes the parameter setting and why some of them were chosen. It also describes other preparations like how the training and test sets are divided and from which companies they are created. How the evaluation of the system is performed is also described in this chapter.

5.1 Evaluation methods

The purpose of this section is to describe the evaluation methods used for the experiments presented in chapter 6. The evaluations of the training sets and the classifier are mainly performed with the precision, recall and the F-Measure, while the evaluation of the trading engine are mainly done by looking at the average percentage return per trade.

5.1.1 Direct comparison of Manually Labeled Set with Automatically Generated Sets

One of the tests that are performed is to directly compare the manually labeled set with the automatically labeled sets. This is done by comparing the positive documents in the automatically labeled sets with the positive documents in the manually labeled and the negative documents in one with the negative documents in the other. Precision and recall are used to find the F-Measure for the positive and negative documents in the automatically labeled sets. Precision for positive documents are found by dividing the number of correctly labeled positive (true positive) documents with all documents labeled as positive (some negative and neutral document might be wrongly labeled as positive). Recall for positive documents is found by dividing the number of correctly labeled positive documents on all the documents that should have been labeled as positive. Precision and recall for negative documents are found in the same way, only difference being that negative documents are used instead of positive. Then the combined precision and recall for positive and negative documents are calculated. The F-Measure used as an indicator of how similar the manually labeled set is with the automatically labeled set are then calculated from the combined precision and recall scores.

5.1.2 Classifier Evaluation

Classifier evaluation is done in two ways. One is to evaluate it with a test set from the automatically labeled set, and the other is to evaluate it with the manually labeled set. Both methods are done the same way. They compare the predicted labels given by the classifier with the labels in the test set that are labeled automatically and the labels in the manually labeled set. The comparison is done the same way as in the above section. The precision and recall is found for the positive and the negative documents, then they are combined and a F-Measure is found from this combined values.

5.1.3 Evaluation of Simulated Stock Trading

When evaluating the news based trading engine it should be compared with a random walk based trader, and it should perform better for it to be of any value. This means that it should on average have positive returns (profit) on its trades. This is however not enough, it should also be compared with the "buy and hold" strategy, and it should preferably also outperform this one.

Some important values are the return, percentage gain or loss, for each trade with these strategies, the number of trades each of them has performed, and also the maximum possible return to get on these trades is of interest. Some useful statistic for comparison found by these values average return on each trade for each of the strategies, and the portion of the maximum possible return they have managed to get. All these values are the average of multiple training sets.

5.2 Document Preprocessing and labeling

The preprocessing step includes stop-word removal and stemming. It removes documents with less than 25 features, short news articles are removed. All features that occur in less than 5 documents are removed from the feature vocabulary. The data sets used in the experiments are created by the labeling method one, which are described in section 4.3.1. The results shown in the experiment chapter shows the average score of multiple different training sets. The training sets are created by looking at price data from only one day into the future and all the way up to five days.

5.3 Training and Test Sets

To get a correct analysis of how the system works it is important to divide the prepared documents into separate training and testing sets. The number of document in each labeled data set in usually somewhere between 2000 and 2600 (never more than 2600) depending on how many is removed by the document elimination process. The classifier evaluation simply divides the prepared documents into two sets. Typically 70% of the documents are given to the training set while the remaining 30% are given to the testing set, which is also how they are divided in this thesis. This is mostly how it is done for the training and test sets for the trading engine too. However there is one exception when the refining method two (see section 4.5.3) is used. This is because it removes documents to make the clusters better. Those documents that it removes are added back to the test set (not to the training set). If they were not added back the result would not be realistic since this process can’t be replicated if news articles not included in the prepared data set were to be tested. This means that results from the classifier evaluation of refining method two is probably a little better than what it is in reality if new unlabeled documents were to be classified by it. If they however were to be added for the classifier testing, the result would be worse than they truly are because the removed documents are very likely to wrongly labeled. The reason why they are likely to be wrongly labeled is that label refining method two removed them instead of moving them to a different cluster, thus they are still labeled with their original label and not relabeled with a different label.

5.4 Training Set Sources: Multiple Companies

All the experiments performed on the system developed in this thesis are done with data sets created from multiple companies from the same field. The classifiers are also trained on these training sets created from multiple companies. This means that one classifier classifies news stories for multiple companies after it is trained.

The reason why this is done is to obtain a larger data set. Few of the companies have enough news stories published about them to get a data set of acceptable size. The classification results from these sets are a little worse than data sets created from a single company that has enough news published about it. FIGURE 5.1 shows that a training set created only by news articles about Statoil (STL) performs much better than training sets created by multiple companies. However, when another company than Statoil was chosen, a company with much less published news articles, then the results would be much worse. This means that companies about which too few news articles are published still can get a classifier to classify its news articles if that classifier was trained on news articles from the same field as that company.

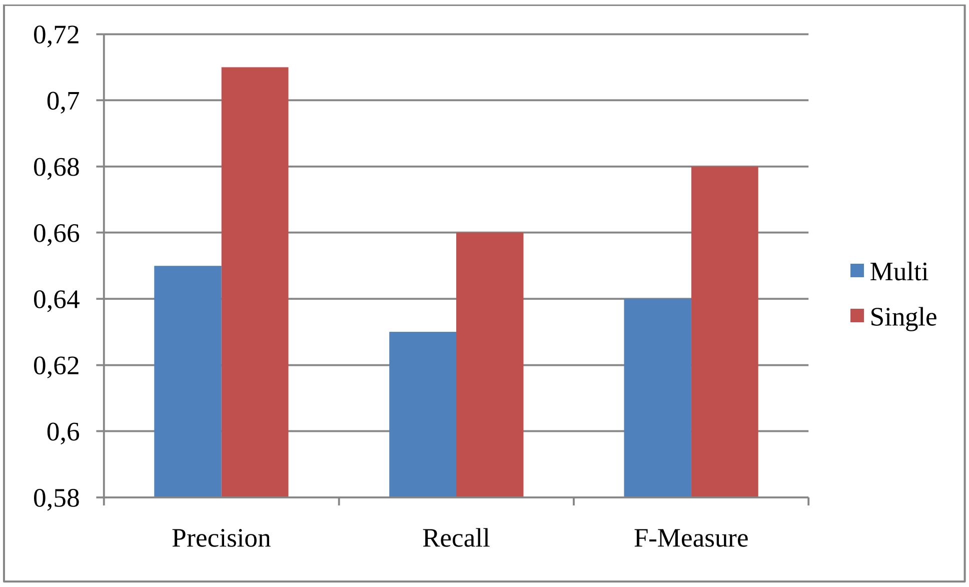


FIGURE 5.1: Comparison of training sets with multiple and single companies (single = Statoil)

FIGURE 5.1 Shows how a classifier trained with a training set generated from multiple companies (data set labeling method one is used with α=0.01 and β=0.02) compares against a classifier trained with a training set generated from only one company(company is Statoil, and parameters are α=0.01 and β=0.02). As seen in the figure, there is only 0.04 points difference between the F-Measure of the two methods.

By going for this larger data set the result is probably somewhat worse, but they should yield much more steady results than what a smaller data set would. The companies that are chosen to create a labeled data set are all companies from the oil business. That they all are in the same field should lessen the penalty of using multiple companies somewhat. The companies used in creating the data sets are “BW Offshore Limited” (BWO), “DNO International” (DNO), “Frontline” (FRO), “Petroleum Geo-Services” (PGS), “Seadrill” (SDRL), “Sevan Marine” (SEVAN), “Siem Offshore” (SIOFF), “Statoil” (STL) and “TGS-NOPEC Geophysical Company” (TGS). They are all companies found on Oslo stock exchange.

5.5 Feature Comparison

Feature comparison is performed with the goal of finding the best feature type. The best feature is then to be use in the experiments in chapter 6. The implemented features are only unigrams and bigrams, and the feature reduction methods are either choosing the n number of features with the highest chi-square value or reducing the number of features by using the SVD method. The feature type that is chosen is bigrams. The reason for this is as FIGURE 5.2, FIGURE 5.3 and FIGURE 5.4 show, that it performs overall better unigrams and the combinations unigrams and bigrams. The scores that are shown on these charts are the average values for positive and negative documents since they are of most interest, the performance on classifying neutral documents are excluded.

For this test the SVM parameter *cost* is set to 3.6 and the *gamma* parameter is set to 1.7. These two variables where chosen by some initial empirical testing. However, in the next section some slightly different variables are found by a more thorough test, and they are used later in the experiments. These The classifiers are then trained and run 500 times on a document collection that are randomly divided in training and test sets each time to find the average statistical evaluation values. Also the label refinement method-one is used and the training set is created by method one over 1 day, where parameter α is 0.01 and parameter β is 0.02. These parameters where found to produce a data set with a good dissolution of positive, neutral and negative documents. If they get to high, the number of documents labeled as positive and negative gets very low. The price trend timing method-one is used, which means the trend is started right before the news is published.

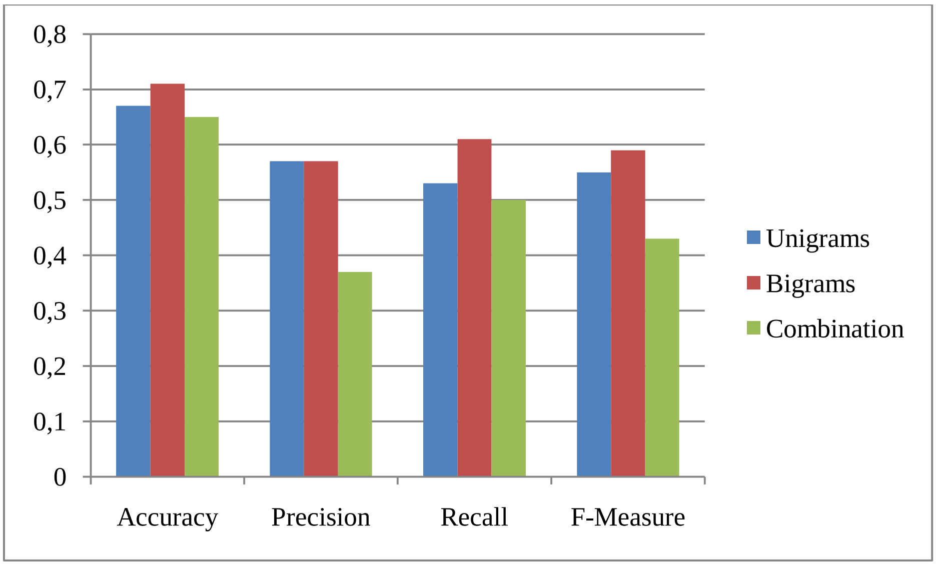


FIGURE 5.2: Feature comparison – CHI reduction 2000 features

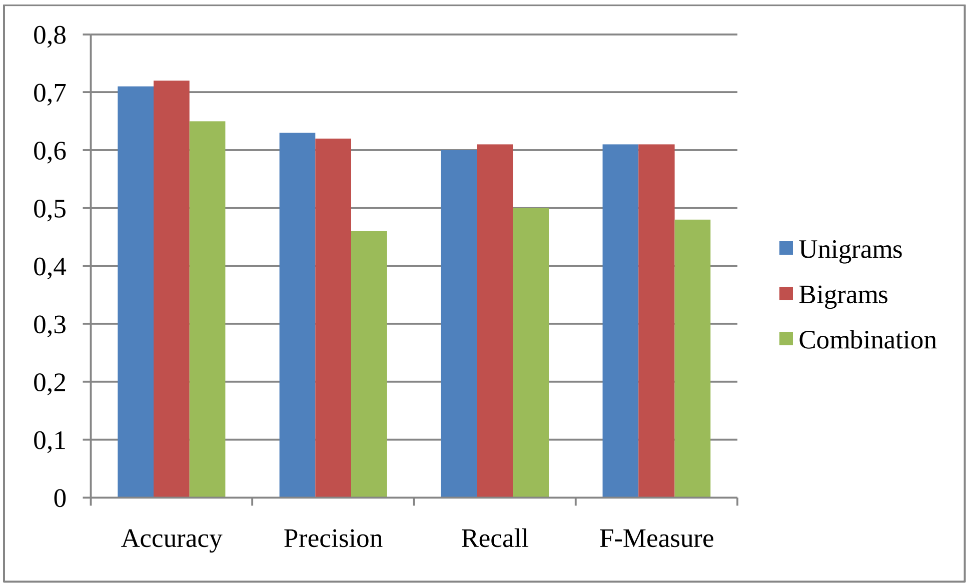


FIGURE 5.3: Feature comparison – SVD reduction 400 features

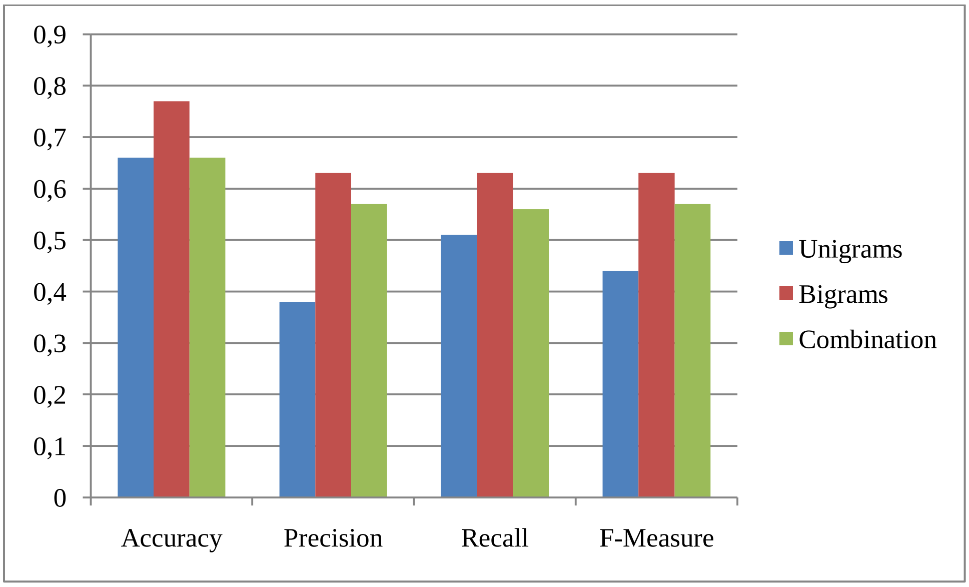


FIGURE 5.4: Feature comparison – SVD reduction 1000 features

The reason why bigrams performs better is probably that bigrams contain some information on the sentence structure, which might be important in some cases, while unigrams has lost all this type of information. As mentioned in section 2.2.2 under bigrams, a classifier using unigrams will classify the two sentences, “from buy to sell” and “from sell to buy”, as the same, while a classifier using bigrams will be able to distinguish the two sentences.

By following this logical trail, it should be able to improve the results even more by using trigrams, which are generally the highest type of N-Gram used in natural language processing. However, this will generate a huge amount of features, and will also require a larger training set than bigrams does. Even by only using bigrams the number of features grows significantly from when unigrams are used. Trigrams are therefore not experimented with in this thesis.

5.6 Classifier Parameter Tuning

The SVM classifier uses, as mentioned in section 4.6, a RBF kernel. This means that the parameters cost and gamma has to be set, and the choice of these parameters can have a big impact on the classifier performance. Therefore some parameter tuning has to be done.

The training set is prepared the same way as in the above section about feature comparison, and as a result of that section bigrams are used as features. The result from some different parameter combinations can be seen in FIGURE 5.5. Each hexagon in that figure shows the average accuracy result over five turns for a parameter configuration test. The parameter values chosen for the experiments in chapter 6 are for gamma 2.3 and for cost 3.5.

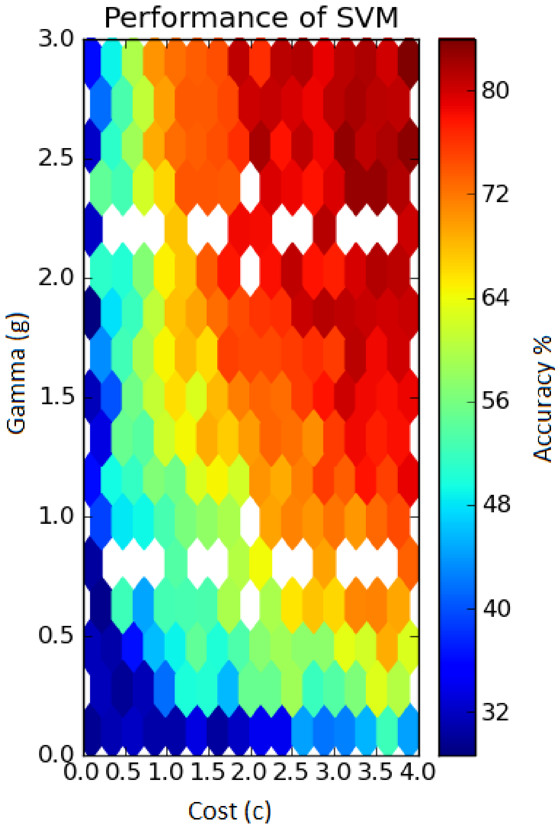


FIGURE 5.5: SVM Parameter Tuning – white spots are parameter configurations that are not tested

6 Experiments, Results and Analysis

This chapter describes experiments performed to investigate our hypothesis introduced in section 1.2, and to discover how well the system performs. This system should preferably be able to classify documents with their correct labels, and hopefully it should give a positive return when trading with the classified news articles. All this is conditioned on that the system is able to learn to classify news articles by training on an automatically created training set.

The first experiment investigates the importance of the price trend timing when labeling news articles. The second experiment investigates the label refining methods. Do the refining methods help, and is one better than the others? These are some questions answered in experiment two. The third experiment looks into how well the system does at simulated trading. Does the system manage to get positive returns on its trades, and how well does it perform compared to the market return and a random trader? These are questions answered in experiment three.

The charts that show the result from the following experiments some terminologies that has to be explained. Most of the charts mentions basic, K-Means, method one, and method two. Basic shows the results from the basic labeling technique without label refining while K-Means, method one and method two shows results from the three label refining methods. Most of the charts also mention trend before (trend timing method "before) and trend after (trend timing method "after"). The results for trend before shows how well training sets created by trend timing method "before" performs while trend after shows the results from training sets created by trend timing method "after". There are created 5 different labeled data sets for each of the two trend timing methods and the results shown in the charts are the average over for these different datasets. The results for each of the labeling methods basic, K-Means, method one and method two are the average value of 500 rounds on each of them. The training- and testing- sets are randomly generated with 70% of the documents in the training sets and the remaining 30% in the testing sets for each new round.

6.1 Experiment 1: Timing of price trends for labeling

This experiment investigates the importance of timing of the price trend when it is used for labeling the training sets. The price trend timing is mentioned in section 4.3.4. The purpose of this experiment is to investigate hypothesis 5. It states that labeling of news articles by using price trends that start a little before the news is published gives more correct labels than when the trend is started right after.

This experiment first compares data sets created by the two different timing methods with the manually labeled set. Then classifiers trained on training sets created by the "before" trend timing method and classifiers trained on sets created by the "after" trend timing method are evaluated on how good they are at classifying the manually labeled set.

6.1.1 Results

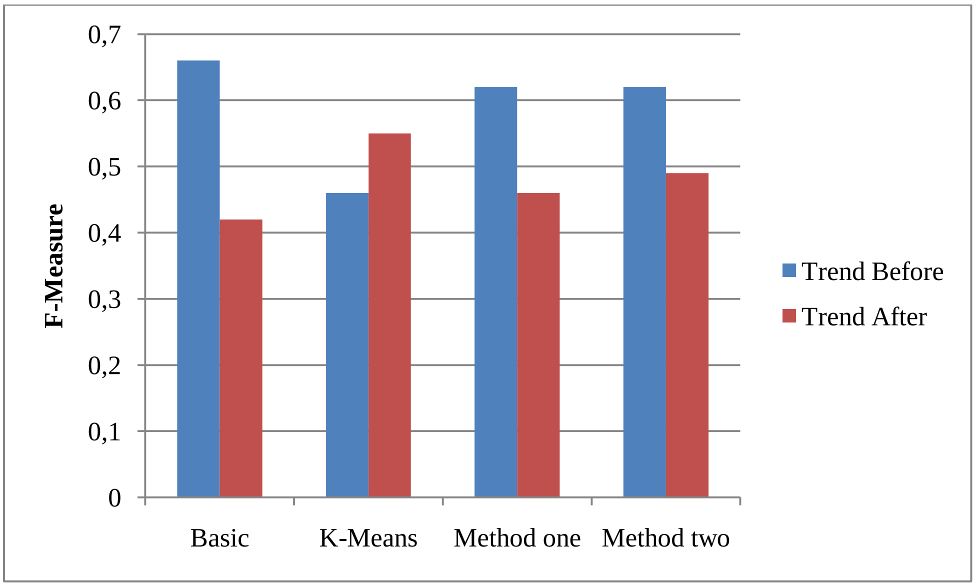


FIGURE 6.1: Comparing timing method “before” and “after” with the manually labeled set.

The results in FIGURE 6.1 show how the automatically created training sets compares with the manually labeled set. Results for both data sets labeled by price trend method “before”, and price trend method “after” when compared with the manually labeled set are shown in the figure. It also shows the results for the basic labeling technique, and for the three different refining methods (K-Means, method one, and method two).

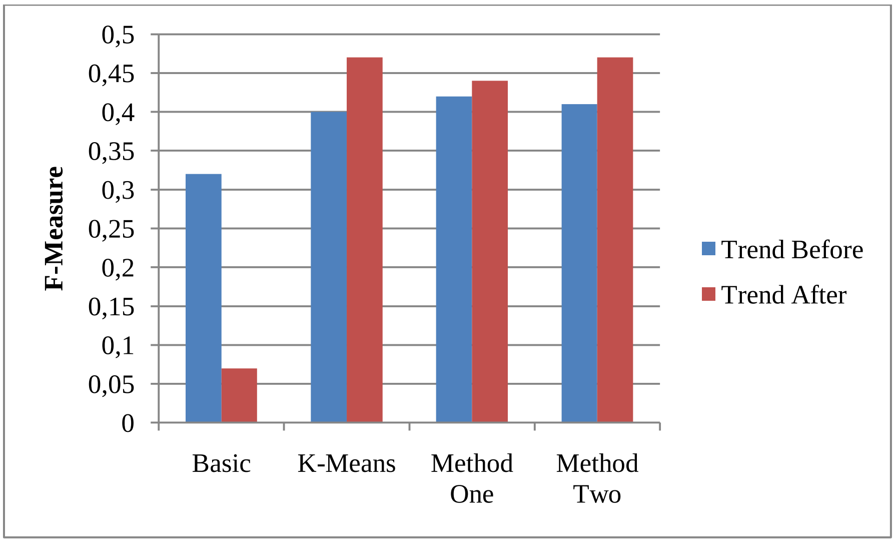


FIGURE 6.2: Classifying manually labeled data set

FIGURE 6.2 shows how good classifiers trained on automatically labeled training sets are at classifying the manually labeled set. It shows how good the labels that are predicted by the classifier are compared to the labels given manually.

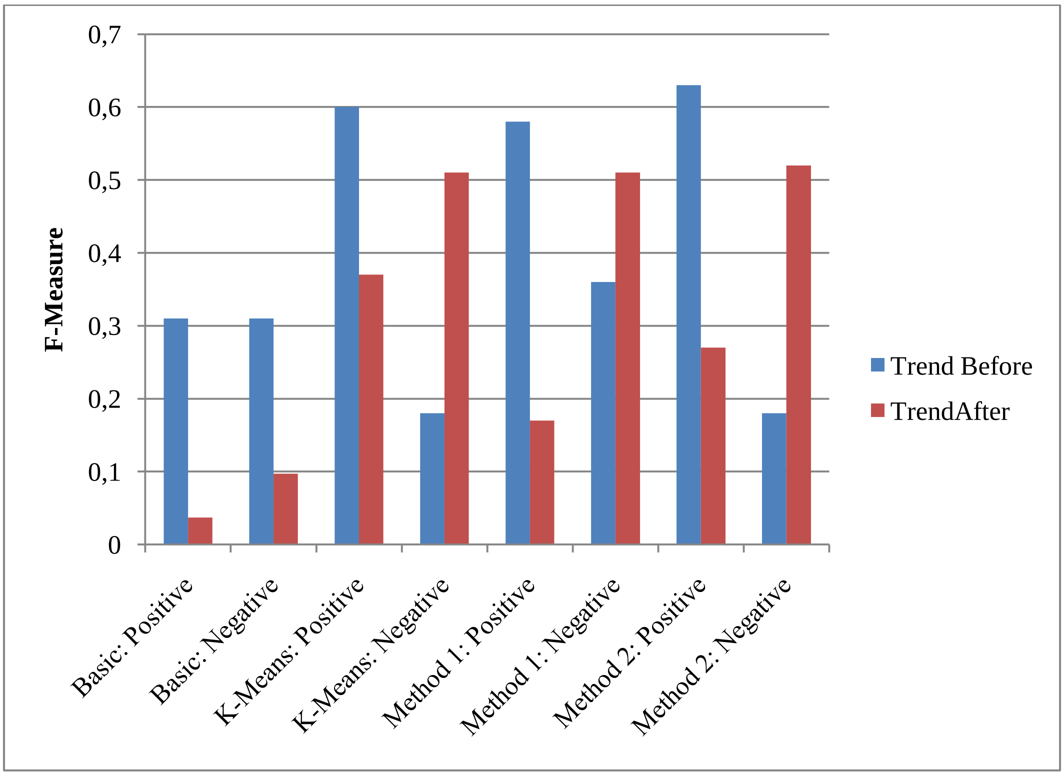


FIGURE 6.3: Classifying manually labeled data set – performance for positive and negative documents

FIGURE 6.3 is much the same as FIGURE 6.2, only difference is that the former instead of showing the average score for the mixture of positive and negative labeled documents, it separate the test sets into two subsets, the positive and the negative documents. This is done to show how good each of the price trend labeling methods are at classifying positive or negative documents. And as we can see, trend timing method "before" is better at classifying positive documents while the trend timing method "after" seems to be better at classifying negative documents.

6.1.2 Analysis

In this experiment the automatically labeled data sets are first compared directly up against the manually labeled set, then classifiers trained on automatically labeled training sets are evaluated by classifying the manually labeled set. FIGURE 6.1 shows that the price trend timing method "before" seems to be doing somewhat better than the trend timing method "after". One reason why this is so might be that for many news articles when the trend timing method "after" is used the price might adjust itself before the trend timing method "after" has started its trend. This means that this method might miss some articles because it starts too late. This is very likely to be the case when daily prices are used, as it was in this experiment.

In FIGURE 6.2 we can see that when classifiers are trained on data sets labeled by the basic method, and not with the label refining methods, they perform much better on data sets that used the price trend timing method "before". However, when the label refining methods are used, both price timing methods are improved, especially the price trend timing method "after", and they become much closer to each other in performance. In the same figure we can see that when the label refining methods are used it might look like that the trend timing method "after" becomes better than the other method. However, they are as mentioned very close in performance, but the trend timing method "after" is slightly better with all the label refining methods. One point that is important to keep in mind is that the manually labeled set is fairly small; it consists of only 81 documents. This means that when evaluations done with the manually labeled set returns results that are close to each other we should be careful to generalize from these results. This is the case with the refining methods in FIGURE 6.2, stating which refining method that is the best cannot be done with any certainty.

In both FIGURE 6.1 and FIGURE 6.2 when only the basic labeling technique is used, the price trend timing method “before” clearly performs better than the price trend timing method “after”. This indicates that the price trend timing is important for the labeling methods performance. The reason why this method is better is probably, as mentioned, that the stock price adjust itself quickly after many of the news articles, which is something this technique still manages to capture in its trend but the other method is too late to capture.

When the label refining methods are used, the difference between the two methods disperses in FIGURE 6.2. However, in FIGURE 6.3 we see that there is a huge difference between the two methods. The price trend timing method “before” is much better at classifying positive documents, while the trend timing method “after” is much better at classifying negative documents. The reason for this might be that people react faster to positive news, and a little slower to negative news. This means that a positive trend might still go up for some time after a negative news is published before the stock price adjusts itself, and this will make the trend calculation method used in this thesis unable to capture this late change. This might not be true for extremely negative news articles, but for more ordinary negative news it might be true. Most people are reluctant to go back on decisions they have made; it takes some time before they change their beliefs about it. The reason for this is the confirmation basis (Plous, 1993) which gives people the tendency to favor information that confirms their preconceptions or hypotheses and disregard evidence that contradicts their beliefs. The confirmation bias is a result of cognitive dissonance (Festinger, 1957) which is an uncomfortable feeling caused by holding conflicting ideas/beliefs simultaneously. This, together with the fact that there are more people that buy stocks than there are people short selling stocks strengthens the speculations that people react slower to negative news than to positive news.

The timing of the price trend when labeling news articles with it is clearly important. However, when the label refining methods are used the two trend timing methods become equally good on average, but they are good at different things. If the label refining methods are included, then it means that hypothesis 5 is likely to be false. If, on the other hand, only the basic labeling method is used, and not the label refining methods, then the price trend timing method “before” performs the best. If this is the case, then the hypothesis 5 is likely to be correct. Since the label refining methods are unique to this thesis, none of the other methods in chapter 3 uses anything like it; it should be the performance of the basic labeling method that counts. This means that hypothesis 5 is true; the trend timing method “before” is better than trend timing method “after”. This is clearly shown in FIGURE 6.1 and FIGURE 6.2.

6.2 Experiment 2: Does label refinement help?

This experiment investigates how the label refining techniques perform. Are they worth using? Hypothesis 4 states that labels given to the news documents by the basic labeling method of linking news articles up with their corresponding price trend can be improved by running these documents by a clustering based algorithm. The reason why this should improve the labels is that positive, neutral and negative documents are assumed to be more similar to other documents in the same label group and less similar to the documents in the other groups. The basic labeling technique is assumed to have grouped the documents into three clusters, although with a fair amount of noise. Sending these clusters through a clustering based algorithm should reduce some of this noise, thus improving the labels.

The data sets are first compared directly with the manually labeled set. The data sets that have been refined should not perform much worse than the basic sets and preferable better. The basic and the refined data sets are divided into training and test sets, and then the training sets are used to train the classifiers. These classifiers are then tested both on their corresponding test sets and on the manually labeled set. The refining methods should make the classifiers much better when tested with their corresponding test sets, and they should also be better than the basic labeling method (no label refining) at classifying the manually labeled set.

6.2.1 Results

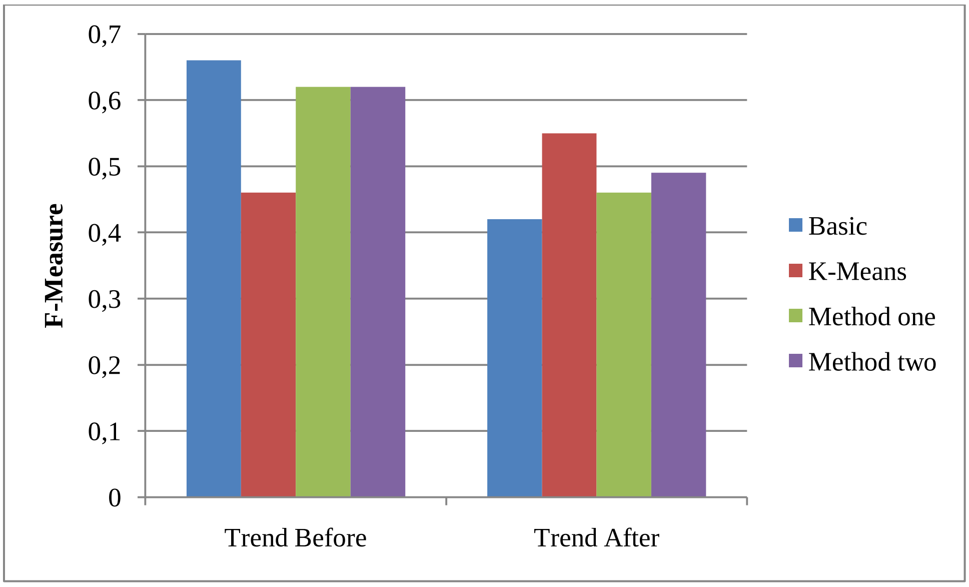


FIGURE 6.4: Compare Manually Labeled Set with Automatically Labeled Sets

FIGURE 6.4 shows the results from the comparison of the automatically generated training sets with the manually labeled set. More specifically, the manually labeled set is compared with data sets generated with the basic labeling method and with sets from each of the three independent refining methods: K-Means, method one, and method two.

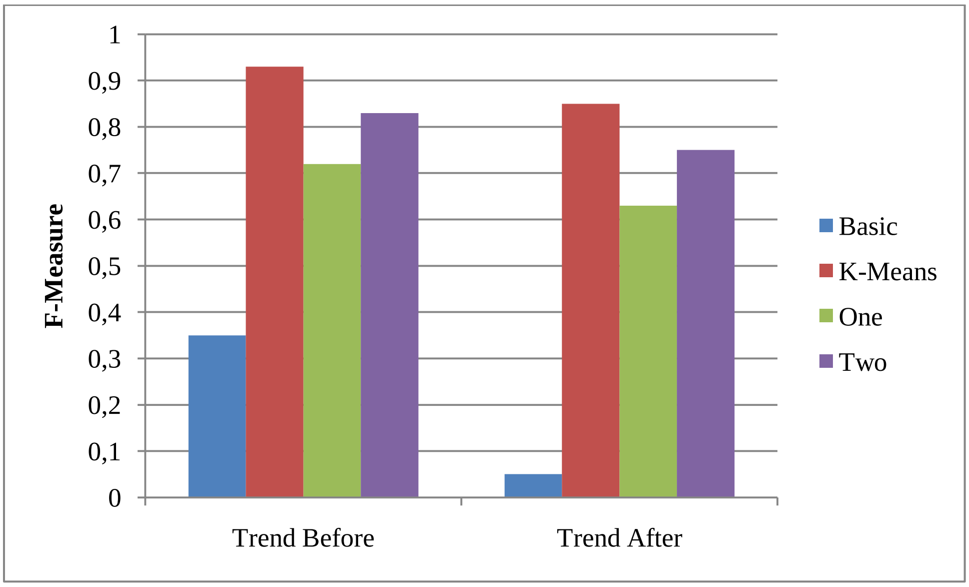


FIGURE 6.5: Classifying Test Set

FIGURE 6.5 shows how the classifiers perform when they are tested on the automatically labeled test sets after they have been trained on the corresponding training sets. The figure shows how good the basic labeling method does, and how well the refining methods perform.

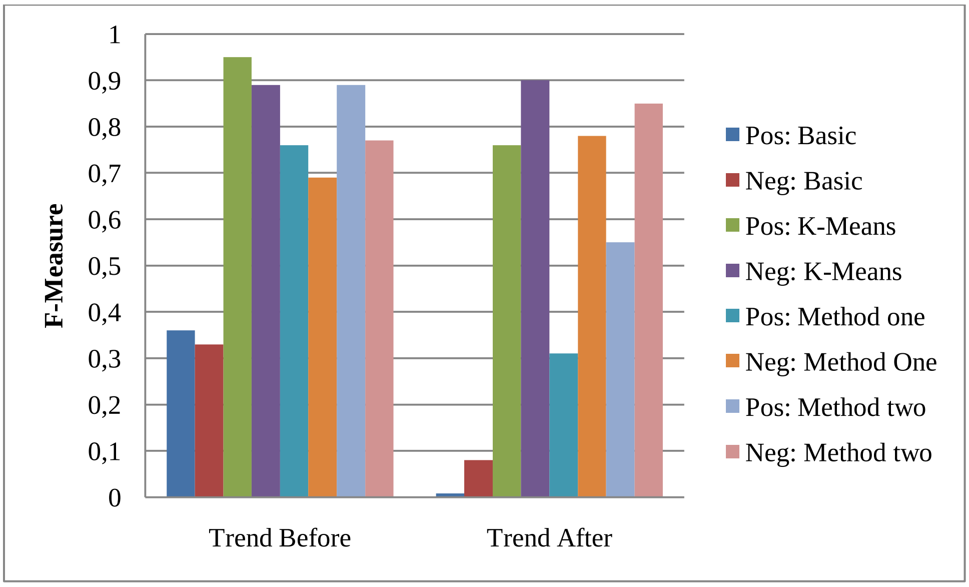


FIGURE 6.6: Classifying Test Set – performance of positive and negative documents

The FIGURE 6.6 shows much the same as FIGURE 6.5 only that it divides the result for the positive and the negative documents to show how the classifier performs on each of those groups. As found in experiment 1, the trend timing method "before" is better at classifying positive documents while the trend timing method "after" is better at negative documents.

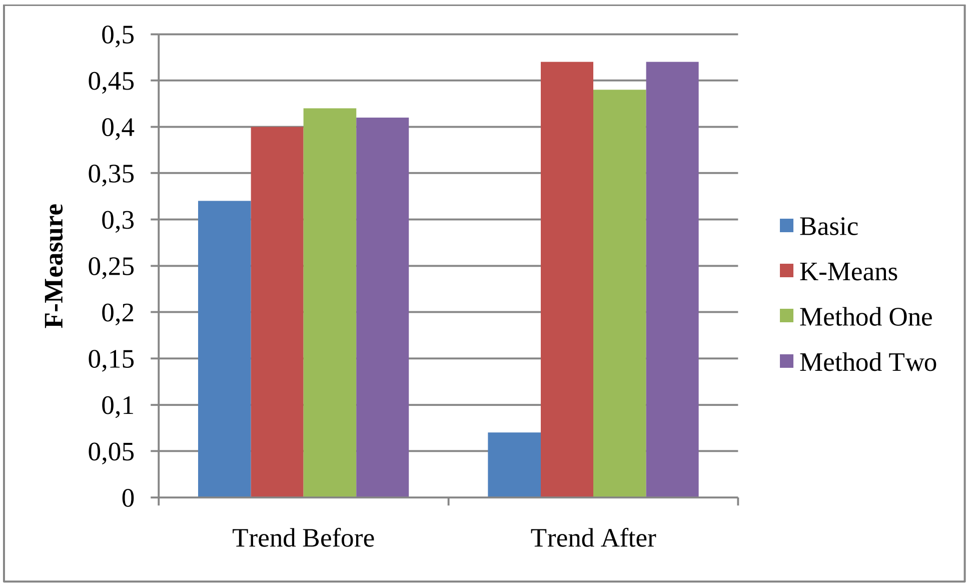


FIGURE 6.7: Classifying manaully labeled data set

FIGURE 6.7 shows how the classifiers perform on the manually labeled set after they have been trained on automatically labeled training sets. The figure shows how good the basic labeling method does, and how well the refining methods perform. FIGURE 6.7 differ from FIGURE 6.5 in that FIGURE 6.7 evaluates how well the classifiers performs on classifying the manually labeled data set while FIGURE 6.5 evaluates how well they performs on classifying their automatically generated test sets.

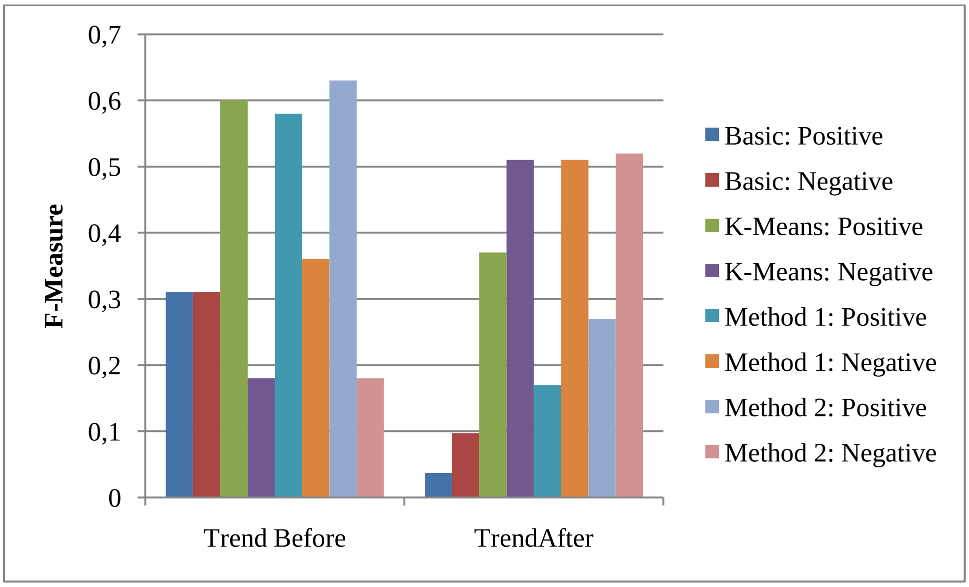


FIGURE 6.8**Error! Bookmark not defined.**: Classifying manually labeled data set – performance of positive and negative documents

FIGURE 6.8**Error! Bookmark not defined.** sows much the same as FIGURE 6.7, only that it divides the result for the positive and the negative documents to show how the classifier performs on each of those groups. As found earlier, the trend timing method “before” is better at classifying positive documents, and the trend timing method “after” is better at negative documents.

6.2.2 Analysis

When the automatically labeled data sets are compared directly with the manually labeled set in FIGURE 6.4 there is no significance difference between the basic labeling and the label refining methods. The manually labeled training set is fairly small, only 81 documents, and all of them are not found by the automatically labeled sets. This means that when there are small differences between the labeling methods, as FIGURE 6.4 illustrates, it cannot be stated with certainty which is the better one.

The refining method might not show any improvement in FIGURE 6.4 when they are compared directly with the manually labeled set, but in FIGURE 6.5 they show some real improvements. However, this is as expected since the positive, neutral and the negative documents have been regrouped into more distinct clusters which makes it easier to train classifiers with them.

The real strength of the refining algorithms is shown in FIGURE 6.7. Here we can see that the label refining methods give a significant improvement when classifying the manually labeled set. Especially the training sets created by the trend timing method “after” have huge performance improvements when they are refined. The reason why the refining methods improve the results are because they do not get any worse when they are directly compared with the manually labeled set, and they have improved their classifier performance because of the more distinct clusters. This means that classifiers trained on refined training sets are more likely to classify news articles with their correct labels than what classifiers trained with training set created only by the basic method. It is important to remember that the manually labeled set is not labeled by an expert, thus not all of the labels might actually be correctly labeled.

Because the refining methods have provided better results, the hypothesis 4 is very likely to be true. This means that the assumptions that similarly labeled documents are more likely to be similar to each other, and likely to be more dissimilar to documents of other labels. Documents in each label group can then be thought of as a cluster, thus, a cluster based algorithm is able to improve the document labels.

This experiment also somewhat verify hypothesis 3 which states that a training set can be automatically created by labeling news articles by using the related stock price trend. The result from FIGURE 6.7 clearly shows that the classifiers trained on training sets with refined labels are able to label more correctly labeled documents than what randomly labeling documents performs on average. Such random labeling would have an F-Measure of 0.33 on average for all the columns. It would be 0.33 and not 0.5 because there are three classes.

6.3 Experiment 3: Trading engine

The main goal of this experiment is to investigate hypotheses 1 and 2. Hypothesis 1 states that a news based trading strategy should outperform a random trader. In other words, it should give a positive return on its trades since it has to be better than a random trader, which, on average, returns zero. Hypothesis 2 states that news based trading method trained with an automatically created training set should perform at the same level or better than a human that trades only by reading news articles.

First, the percentage return per trade for the manually labeled set is computed. After that the average percentage returns per executed trade performed by the different trading methods are computed, and the average percentage return for each bought or short sold stock is also found. Then the average percentage return per trade is compared with the average return of the market (buy hold strategy). All the trades performed in this experiment are done on daily prices. The system is ready to use intraday prices, but they have not been tested mainly due to time constraints. However, the few tests performed on intraday data performed very few trades because much fewer news documents are found. The reason for this is that only news documents published during the stock exchanges opening time is used for trading while the rest are not used to trade with. Since the system performed so few trades with intraday prices the results can't be used with much certainty. One way to solve this could be to test with more companies, or to gather intraday data for a longer duration.

6.3.1 Results

This section shows only the results from each the tests performed, no analysis of the results are performed in this section. It should be noted that for each of the following test, the percentage is shown as values where 0.0 is 0% and 1.0 is 100%.

method 1	% Return per trade
Manually labeled	0.003

TABLE 6.1 Experiment 3 - manually labeled - trading returns

TABLE 6.1 shows how much a trading agent returns on average per trade when it trades by using the manually labeled data set. The news traders using classifiers trained by automatically labeled training sets should preferably perform just as well as this.

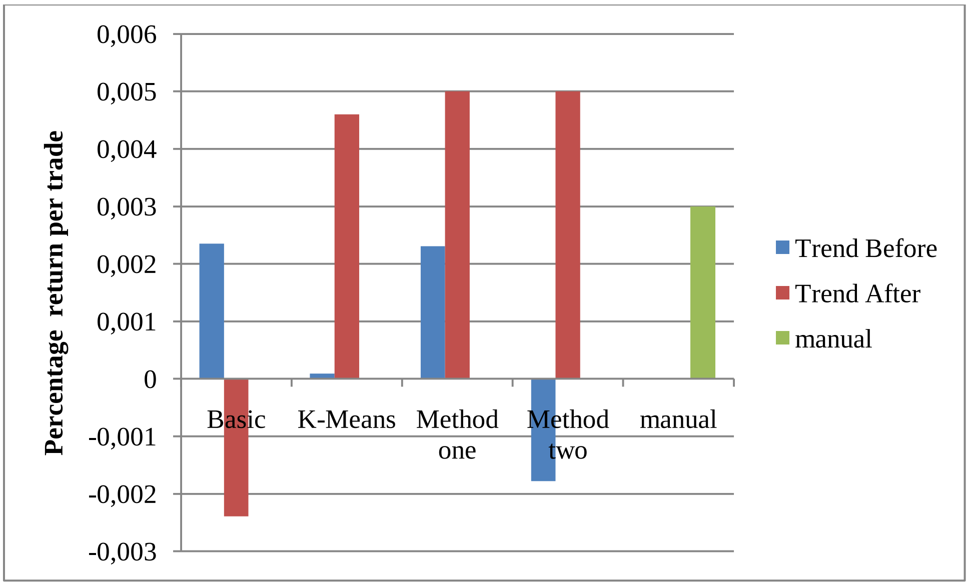


FIGURE 6.8: Average return per trade – performance of both buy and sell together

FIGURE 6.8 shows the average return in percentage per trade for each of the different labeling methods. We can see that in most cases they have a positive percentage return per trade. It also shows the return when trading on the labels from the manually labeled set.

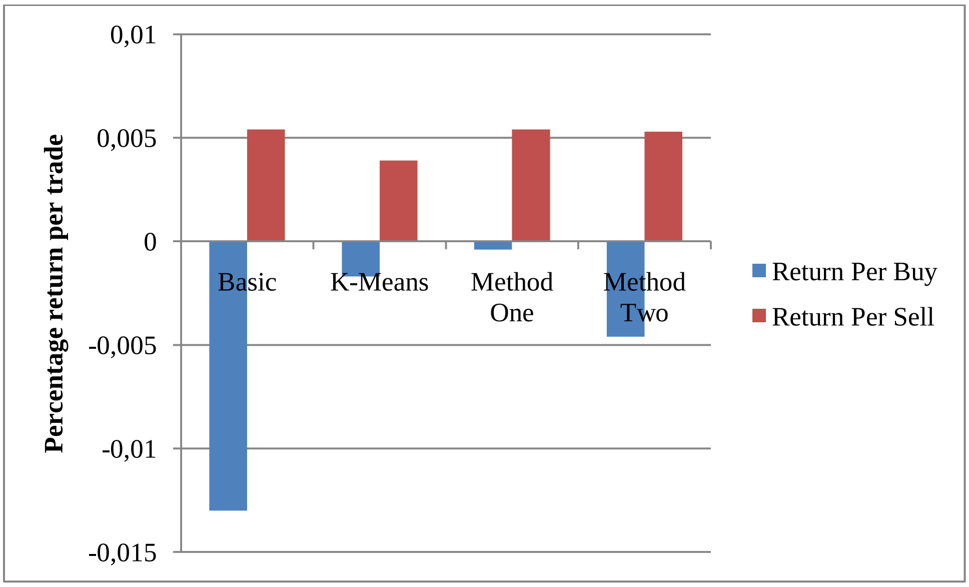


FIGURE 6.9: Average return per trade – timing method before – dividing buy and sell

FIGURE 6.9 shows the average return for each bought and short sold stock trade for trader using classifiers trained data sets labeled by the trend timing method “before”. The figure shows that they clearly perform better when selling on negative news articles than when buying on positive news articles.

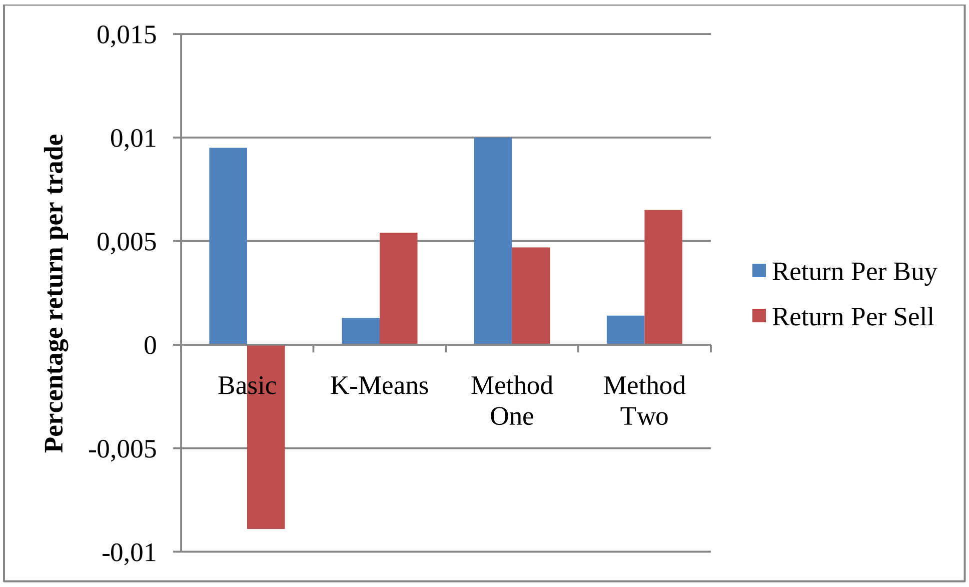


FIGURE 6.10: Average return per trade – timing method after – dividing buy and sell

FIGURE 6.10 shows the average return for each bought and short sold stock trade for trader using classifiers trained data sets labeled by the trend timing method “after”. In all the trades where it buys the returns are positive, and only the basic labeling method is has negative returns when it sells.

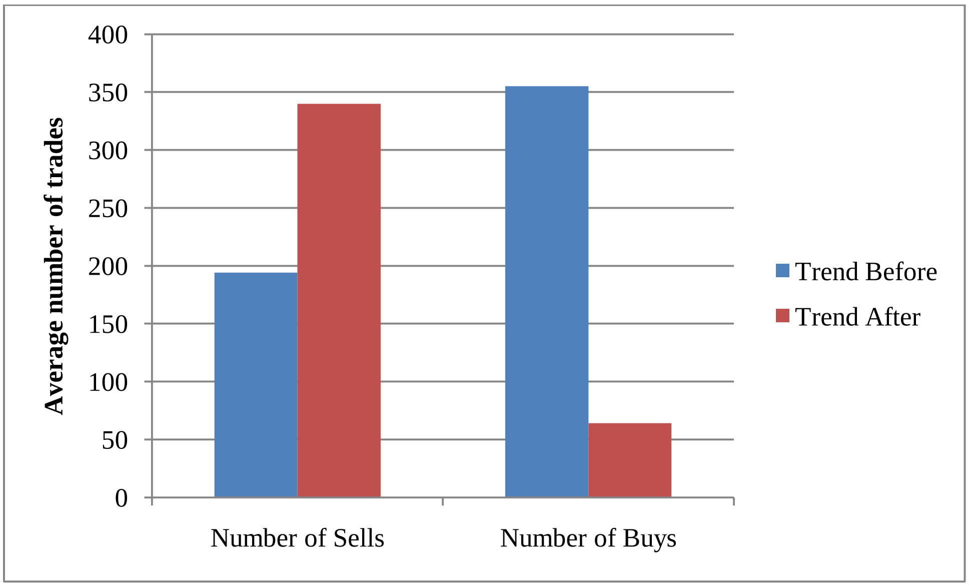


FIGURE 6.11: Average number of trades – timing menthod before and after – buy and sell

FIGURE 6.11 shows how many trades on average the two trend timing methods perform on sales and buys. It clearly shows that the “before” method buys much more than it sells while the “after” method sell much more than it buys. This is in concurrence with the fact that the “before” method performs better at positive documents, while the “after” method performs better at negative documents.

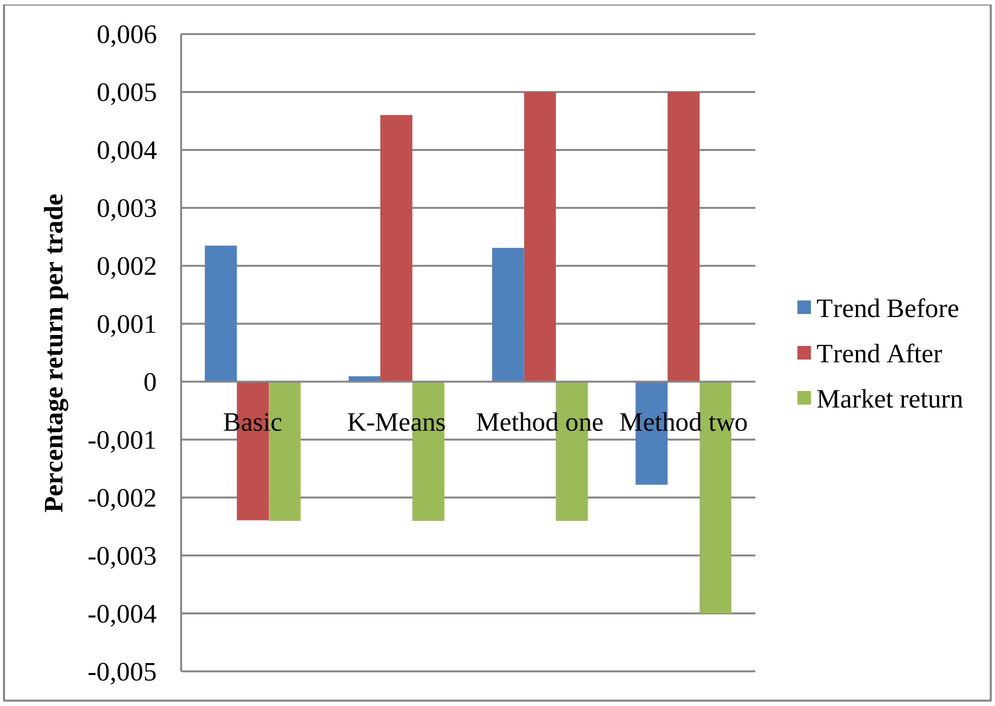


FIGURE 6.12: Average return per trade compared with average market return

FIGURE 6.12 compares the average return for each trade for every method with the average return of the market. The average return of the market is the same value as what the “buy and hold” trade strategy yields.

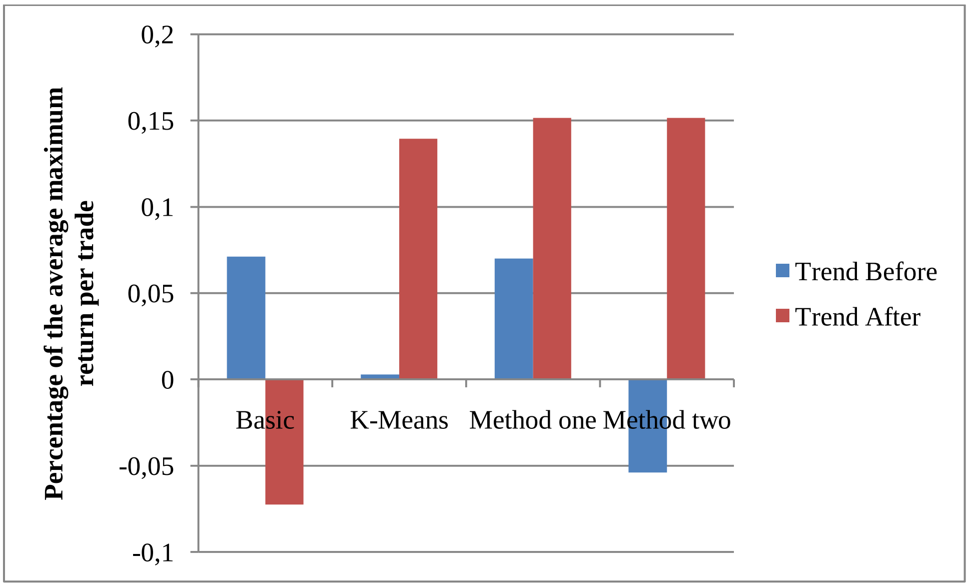


FIGURE 6.13: Percentage of the average maximum possible return per trade

FIGURE 6.13 shows the percentage of the average maximum possible return per trade each of the methods performs. As seen the trend after method manages to return on average 15% of what is maximally possible to return on average for each trade. The maximum possible return is on average 0.033, or 3.33% per trade.

6.3.2 Analysis

In FIGURE 6.8 we can clearly see that most of the trades give positive returns. The trades performed with the label refined data sets which were originally labeled by the trend timing method “after” have returns per trade which is higher than what trading on the manually labeled set gives. None of the other methods gives a return at that level. However, if the trades done on the trend timing method “before” data sets where only allowed to sell, and not to buy, then all those trades would be just as good or better than the manually labeled data set. The reason why trend timing method “before” does so badly when it buys is probably because the trades are done from the first price after the news is published and that daily prices were used. By the time the stock is bought it has already risen the amount it was supposed to since positive news were found to make traders react faster. When it comes to it, hypothesis 2 is confirmed, or at least partly confirmed. The news traders trading on the outputs from classifiers trained on automatically labeled training sets performs in some cases just as god as the manually labeled set. If the trades were to be done with intraday data, it might improve the results of the trend timing method “before” since it probably would buy stocks before they went all the way up in price.

In FIGURE 6.10 we see that the trend timing method “after” manages to get an average positive return when it buys stocks. The reason why it manages to do this is probably that it captures some of the few positive news documents that traders are slow to react to and learn to recognize them. While the “before” methods captures all the positive documents that traders react fast on.

In FIGURE 6.12 we can see that the news based trading system never does worse on average than the average market return. This means that the news based trader is likely to be better than a “buy and hold” based trader. However, the “buy and hold” method always returned negative results in these tests. It is not certain that the news based trader would still be better when the market returns positive results.

FIGURE 6.13 shows that some of the best methods, the label refining methods on data sets created with trend timing method “after”, manages to give a return that is approximately 15% of what the maximally possible average return per trade is. This is clearly some promising results that shows that there is some merits to an automatically news based trading system.

Given the positive returns from the trades performed by this system, hypothesis 1 stating that this kind of trading method is better than a random one is likely to be true, if the earlier results from similar system, some of which mentioned in chapter 3, are taken into consideration. Then the likelihood of hypothesis 1 being true is even greater since they also have got positive returns on their systems.

Note that this trading strategy is extremely simple. It acquires a stock (buy or short sell) and then simply sells it after a fixed duration, one day in this case. This means that the gained profits could be raised by employing better trading strategies, and losses could be lessened by adding in some risk reduction techniques (such as some simple support lines).

By looking at FIGURE 6.9 and FIGURE 6.10 a suggestion for an improved trading agent can be discovered. First the trading agent is extended with two classifiers instead of only one. The first classifier is trained on a label refined training set created by the trend timing method “before”, and the second classifier is trained on a label refined training set created by the trend timing method “after”. Then the strategy for buying stocks is to only buy when the classifier trained on the training set created by the trend method “after” classifies news articles as positive. When the trend method “before” classifies a news article as positive, then the stock is not bought. This is because, as seen in FIGURE 6.10 and FIGURE 6.9, only the data sets created by the trend labeling method “after” gives positive returns on average when buying stocks. It short sells stocks whenever any of the classifiers classifies a news article as negative. Then this trader might be mightily improved over the traders tested in this experiment. The reason for this is, as seen in FIGURE 6.10 and FIGURE 6.9, that both of the trend timing methods gives positive returns when short selling stocks. This strategy should improve the trading returns when daily prices are used. When intraday prices are used, it is likely that the returns from buying stocks with a trader trained on the trend timing method “after” is able to get positive returns when buying stocks. The reason why this might be is that when intraday prices are used the time duration between the news article publication time and the time of the trade is much shorter than with daily prices.

7 Conclusion and Future Work

This chapter will briefly review the main aspects of the thesis and important results and concluding remarks are provided accordingly. Suggestions for future work will also be stated.

7.1 Overview of Thesis

The main objectives of this thesis is to study existing systems that automatically analyses financial news articles to predict future price actions, to investigate text mining methods that might be of use for such systems, and at last to design and implement a system for this purpose. The system that is to be designed and implemented should be entirely automated, only some of the evaluations parts for testing the system can have some manual parts (manually labeled data set for evaluation). This system should be able to automatically learn to find correlations between features in the news articles and the changes in the stock prices.

This thesis provides some background information about relevant trading theory and some important and relevant text mining techniques. This background information is helpful for understanding the rest of this thesis. A review of relevant news based trading systems is provided. Most of these systems have certain important parts in common. They have a classifier component that categorizes news articles depending on how they affect the price actions. For the classifier to work they have to generate a labeled training set. The technique used to generate this set is different in most of the systems. The news documents must also be preprocessed and features has to be extracted and selected from them for the classifier to have something to work on. Most of the relevant systems also add a trading engine which uses the categories of the news articles to make a decision.

In the practical part of this thesis, a news based trading decision system was designed and implemented. The approach for designing this system is much the same as the general approach common to most of the earlier system. However, some different and new elements where included. The most notably, a clustering based label refining step included in an attempt to improve the labels given by the basic price trend labeling method. The thesis goes then on to describe the preparation steps before the experiments can be performed. In this preparation stage the type of features to be used is selected (bigrams), SVM parameters are optimized, document preprocessing parameters are set, and experiment evaluation methods are described. The thesis then goes on to describe the experiments that are performed. Experiment 1 has the purpose of investigating the performance difference between the trend timing method “after” and the trend timing method “before” for generating labeled data sets. Experiment 2’s purpose is to find out if the label refining methods truly improves data sets labeled with the basic method of using price trends. The last experiment, experiment 3, has the purpose of investigating how the system performs on simulated trading.

7.2 Concluding Remarks

In experiment 1 which investigates hypothesis 5 (i.e. trend timing method “before” is better than trend timing method “after”), some interesting results are discovered. In addition to supporting hypothesis 5 (only when the refining method are not used), it also returns some surprising differences between the two methods. The trend timing method “before” is much better at correctly labeling positive documents than it is as labeling negative documents, and trend timing method “after” is much better at correctly labeling negative news articles than it is at labeling positive news articles. See section 6.1.2 for experiment analysis.

The main purpose of experiment 2 is to investigate hypothesis 4 (i.e. label refining methods improves the labels given by the basic price trend labeling method). This experiment clearly shows that label refining helps. In FIGURE 6.5, where the classifier is tested on a automatically labeled test set, the F-Measure goes from 0.35 with the basic labeling to 0.72 with label refining method two when trend timing method “before” is used. When trend timing method after is used the F-Measure goes from 0.05 to 0.63. In FIGURE 6.7, where the classifier are tested on the manually labeled data set, the F-Measure goes from 0.32 with the basic labeling to 0.42 with label refining method two when trend timing method “before” is used. When trend timing method after is used the F-Measure goes from 0.07 to 0.44. This clearly shows that label refining improves the labels labeled by the basic price trend method. See section 6.2.2 for experiment analysis.

Experiment 3 simulates trades by using the labels given by the trained classifier. Its main purpose is to investigate hypothesis 1 and 2 (the system should perform better than random trading and it should perform on the same level or better as trading with the manually labeled set). Both hypothesizes are supported by the evidence found in this experiment. The results show that some of the methods manage to get 0.5% return on average for each trade they perform. Which is promising given that each trade is only lasting one day. This return is 15% of what the maximum possible return is. See section 6.3.2 for experiment analysis.

The news based trade decision support system proposed in this thesis is shown to be able to do some good trading decisions. Systems like this can therefore be very beneficial for traders as a tool to help making better trading decisions. With such a model it is easier to foresee future behaviors and movement of stock prices. Thus it is also easier to take correct actions immediately and act properly in trading decisions to gain more profits and prevent losses.

7.3 Future Work

Automatic news based trading decision systems are a small but growing research field, thus there are many aspects that can be investigated further. With regard to system developed in this thesis the following issues can be considered to be the primary ones that should be investigated in future works:

1. At the end of section 6.3.2 a possible improvement for classifying news articles are proposed. This improvement tries to profit on the finding that data sets generated with trend timing method “after” is better at correctly labeling negative news articles while sets generated with trend timing method “before” is better at correctly labeling positive news articles. A classifier method that takes advantage of this could be able to gain higher profits than the method developed in this thesis.
2. The classifier method used in this thesis classifies, positive, neutral, and negative articles. A possible improvement to this could be to divide this single classifier into two classifiers. First, a classifier trained to classify news articles as “affecting trade volume” or “not affecting trade volume”, then those news articles classified as “affecting trade volume” is sent to a second classifier which classify the documents as either “positive” or “negative”. This means that news articles with little impact on trade volume are removed, and positive and negative news articles are only found among those news articles with a high impact on the stock trading volume. This should probably improve the precision of news classified as positive or negative, thus the average return per trade should be larger. However, the recall will probably less, and as a consequence less trades will be performed.
3. Thorough evaluations with intraday data should be performed. The system developed in this thesis is ready for evaluations with intraday data, but it needs more data to be performed. This could be done by using intraday data over a longer period (this was not possible in this thesis because only one year with intraday data is gathered) or a labeled data set could be generated by using many more companies.
4. The trading strategy could be improved. The strategy used in this thesis only acquire a stock for a fixed time duration (one day) then liquidates it. This strategy could easily be improved by using some support lines and to control when to liquidate. Or the news based trading

method could be improved by including some more advanced technical- and fundamental analysis methods. This would very likely give a much higher return on each trade.

5. Conduction comparative studies against other types of trading method. Compare the developed news based trader with trading systems based on other techniques, such as technical- or fundamental analysis methods. It would be interesting to see how trading by using news stories compares with other kinds of trading strategies.
6. This thesis uses singular value decomposition (SVD) to find latent semantic meanings and as a feature reduction method. Topic models (LDA) was supposed to be included as an alternative. However, duo to time constraints, this was not done. It would therefore be interesting to investigate this to see if it gives some improvements. Using contextual clues, topic models can both connect words with similar meanings and distinguish between uses of words with multiple meanings. SVD cannot distinguish between words with multiple meanings.

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Appendix A: News Article Example

The following text shows an example of a news article that is downloaded from internet and stored locally. It is written in Norwegian.

```
<doc>
<date>
26/03-2010
</date>

<time>
11:31:39
</time>

<source_link>
http://www.hegnar.no/bors/energi/article415615.ece
</source_link>

<source>
Hegnar
</source>

<text>
<title>
Statoil kjøper skifergass for 1,5 milliarder kroner
</title>

<body>
Statoil har inngått avtale med partneren Chesapeake om å kjøpe ytterligere
  59.000 acres på Marcellus Shale-formasjonen i USA. Statoils eierandel på
  Marcellus var 600.000 acres før avtalen ble inngått.

Prisen på transaksjonen er estimert til 253 millioner dollar eller i overkant
  av 1,5 milliarder kroner. Prisen per acre er 4.325 dollar.

Statoil inngikk en joint venture-avtale med Chesapeake i 2008 og har rett til
  periodevis å kjøpe seg opp, etterhvert som Chesapeak øker sin eierandel på
  Macellus.

Statoil skriver videre at de ser positivt på produksjonsutviklingen fra 2008
  og frem til i dag. De forventer også å styrke posisjonen sin på Marcellus
  ytterligere i fremtiden, sammen med partneren Chesapeake.

- Vi forventer å nå vårt mål om en produksjon på 50.000 fat oljeekvivalenter
  per dag innen 2012, sier Andy Winkle i en kommentar.

Her finner du mer om
</body>
</text>
</doc>
```

This article was originally labeled as neutral but after it was refined with label refining method one it was relabeled as a positive document. This document is clearly more positive that it is neutral. Note that this is not an opinion from a financial expert.

Word of two characters or less are removed, features (bigrams) that occurs in less than two documents are removed. Stemming is not used in this case because it makes it harder to understand. The following example is the features extracted from the news document above. It shows the feature (bigram) followed by how many times it occurs in this text.

```
[[(u'statoil', u'kjøper'), 1], [(u'for', u'milliarder'), 1],
[(u'ble', u'inngått'), 1], [(u'per', u'dag'), 1], [(u'seg',
u'opp'), 1], [(u'har', u'inngått'), 1], [(u'videre', u'ser'),
1], [(u'statoil', u'har'), 1], [(u'2012', u'sier'), 1],
[(u'2008', u'har'), 1], [(u'ser', u'positivt'), 1], [(u'med',
u'chesapeake'), 1], [(u'oljeekvivalenter', u'per'), 1],
[(u'estimert', u'til'), 1], [(u'dollar', u'statoil'), 1],
[(u'dag', u'innen'), 1], [(u'rett', u'til'), 1], [(u'kjøpe',
u'seg'), 1], [(u'kjøpe', u'ytterligere'), 1], [(u'fra',
u'2008'), 1], [(u'her', u'finner'), 1], [(u'inngått',
u'avtale'), 1], [(u'per', u'acre'), 1], [(u'joint',
u'venture'), 1], [(u'etterhvert', u'som'), 1], [(u'avtalen',
u'ble'), 1], [(u'til', u'dag'), 1], [(u'kroner', u'prisen'),
1], [(u'ytterligere', u'000'), 1], [(u'dollar', u'eller'), 1],
[(u'frem', u'til'), 1], [(u'sin', u'eierandel'), 1],
[(u'skriver', u'videre'), 1], [(u'produksjon', u'000'), 1],
[(u'mål', u'produksjon'), 1], [(u'overkant', u'milliarder'),
1], [(u'000', u'acres'), 2], [(u'har', u'rett'), 1],
[(u'forventer', u'også'), 1], [(u'kroner', u'statoil'), 1],
[(u'til', u'253'), 1], [(u'fat', u'oljeekvivalenter'), 1],
[(u'avtale', u'med'), 2], [(u'600', u'000'), 1],
[(u'milliarder', u'kroner'), 2], [(u'000', u'fat'), 1],
[(u'sammen', u'med'), 1], [(u'millioner', u'dollar'), 1],
[(u'statoil', u'skriver'), 1]]
```

Appendix B: Examples of Evaluation Summaries

This appendix shows some of the evaluation summaries as an example. The data set is generated by labeling method one with trend timing method “after”. The parameters for the labeling method are α=0.01 and β=0.02. All other parameters are the same as in the experiments. The firs examples are from the classifier evaluation. It shows precision, recall, F-Measure, accuracy and crossover. Crossover shows the portion of document in the given cluster that belongs to the other clusters.

Basic	K-Means
___Evaluation C1 pos AUTO____ Accuracy: 0.75379020979 Precision: 0.623777777778 Recall: 0.0100163928474 F-Measure: 0.0196394007816 Crossover: 0: 0.0601111111111 -1: 0.196111111111 ___END OF Evaluation C1 pos AUTO____ ___Evaluation C1 neg AUTO____ Accuracy: 0.638769230769 Precision: 0.415825578414 Recall: 0.135450049705 F-Measure: 0.201008295852 Crossover: 0: 0.298872541204 1: 0.285301880382 ___END OF Evaluation C1 neg AUTO____ ___Evaluation C1 pos MANUAL____ Accuracy: 0.394567901235 Precision: 0.02 Recall: 0.000408163265306 F-Measure: 0.0008 Crossover: ___END OF Evaluation C1 pos MANUAL____ ___Evaluation C1 neg MANUAL____ Accuracy: 0.566172839506 Precision: 0.265614885115 Recall: 0.065625 F-Measure: 0.101862946089 Crossover: 1: 0.574385114885 ___END OF Evaluation C1 neg MANUAL____	___Evaluation C1 pos AUTO____ Accuracy: 0.904727272727 Precision: 0.96882510189 Recall: 0.504772599067 F-Measure: 0.662870309328 Crossover: 0: 0.00923565903409 -1: 0.0219392390758 ___END OF Evaluation C1 pos AUTO____ ___Evaluation C1 neg AUTO____ Accuracy: 0.843552447552 Precision: 0.812810929681 Recall: 0.996843535273 F-Measure: 0.895387370302 Crossover: 0: 0.0752368628009 1: 0.111952207518 ___END OF Evaluation C1 neg AUTO____ ___Evaluation C1 pos MANUAL____ Accuracy: 0.422962962963 Precision: 0.600995060495 Recall: 0.137959183673 F-Measure: 0.223824838518 Crossover: -1: 0.399004939505 ___END OF Evaluation C1 pos MANUAL____ ___Evaluation C1 neg MANUAL____ Accuracy: 0.525185185185 Precision: 0.441951769399 Recall: 0.766875 F-Measure: 0.560592795561 Crossover: 1: 0.558048230601 ___END OF Evaluation C1 neg MANUAL____
Method one	Method two
___Evaluation C1 pos AUTO____ Accuracy: 0.735034965035 Precision: 0.772922485573 Recall: 0.143182001876 F-Measure: 0.241040684965 Crossover: 0: 0.0957448943155 -1: 0.131332620111 ___END OF Evaluation C1 pos AUTO____ ___Evaluation C1 neg AUTO____ Accuracy: 0.689020979021 Precision: 0.639601950952 Recall: 0.986600187281 F-Measure: 0.775926462348 Crossover: 0: 0.060781438664 1: 0.299616610384 ___END OF Evaluation C1 neg AUTO____ ___Evaluation C1 pos MANUAL____ Accuracy: 0.414074074074 Precision: 0.661761904762 Recall: 0.0808163265306 F-Measure: 0.141921187992 Crossover: -1: 0.338238095238 ___END OF Evaluation C1 pos MANUAL____ ___Evaluation C1 neg MANUAL____ Accuracy: 0.496666666667 Precision: 0.42757868693 Recall: 0.8121875 F-Measure: 0.560034904368 Crossover: 1: 0.57242131307 ___END OF Evaluation C1 neg MANUAL____	___Evaluation C1 pos AUTO____ Accuracy: 0.870649819495 Precision: 0.94154153716 Recall: 0.237450074606 F-Measure: 0.377223489463 Crossover: 0: 0.0134031169229 -1: 0.0450553459169 ___END OF Evaluation C1 pos AUTO____ ___Evaluation C1 neg AUTO____ Accuracy: 0.805740072202 Precision: 0.773119184633 Recall: 0.997048890664 F-Measure: 0.870772041586 Crossover: 0: 0.0774106291734 1: 0.149470186193 ___END OF Evaluation C1 neg AUTO____ ___Evaluation C1 pos MANUAL____ Accuracy: 0.417283950617 Precision: 0.784833333333 Recall: 0.0591836734694 F-Measure: 0.108156048084 Crossover: -1: 0.215166666667 ___END OF Evaluation C1 pos MANUAL____ ___Evaluation C1 neg MANUAL____ Accuracy: 0.494074074074 Precision: 0.430936001438 Recall: 0.875625 F-Measure: 0.57748162387 Crossover: 1: 0.569063998562 ___END OF Evaluation C1 neg MANUAL____

The following example shows outputs from the simulated trading on the same data set as in the above example.

Basic	K-Means
Avg return news sel, buy and total 0.552046290817 0.0481437440693 0.600190034886 Avg return news per trade sel, buy 0.00687052010973 0.0175068160252 Avg return market: -2.15499601039 Avg return market per turn: -0.00301478156487 Avg return max posible: 24.5037135955 Avg return max posible per turn: 0.0342800374862 Avg nr news trades sell, buy 80.35 2.75 Avg nr random trades sell, buy 238.3 236.9	Avg return news sel, buy and total 1.91947332912 -0.226910776594 1.69256255252 Avg return news per trade sel, buy 0.0032782370015 -0.00317047333511 Avg return market: -2.1628881747 Avg return market per turn: -0.003026118833 Avg return max posible: 24.6831753315 Avg return max posible per turn: 0.0345344815338 Avg nr news trades sell, buy 585.52 71.57 Avg nr random trades sell, buy 238.56 239.24
Method one	Method two
Avg return news sel, buy and total 2.36817356184 0.258236328338 2.62640989018 Avg return news per trade sel, buy 0.00393947094161 0.00638250935092 Avg return market: -2.10127090845 Avg return market per turn: -0.00294015630555 Avg return max posible: 24.7222880855 Avg return max posible per turn: 0.0345921084758 Avg nr news trades sell, buy 601.14 40.46 Avg nr random trades sell, buy 236.34 240.5	Avg return news sel, buy and total 5.25609705569 0.0267835265719 5.28288058227 Avg return news per trade sel, buy 0.00592149550567 0.000701323031473 Avg return market: -5.39490000666 Avg return market per turn: -0.00539587126349 Avg return max posible: 36.1352339804 Avg return max posible per turn: 0.0361417394935 Avg nr news trades sell, buy 887.63 38.19 Avg nr random trades sell, buy 333.33 333.65